The Flash Crash: The Impact of High Frequency Trading on an Electronic Market*

Andrei Kirilenko Albert S. Kyle

Mehrdad Samadi Tugkan Tuzun

December 10, 2010

Abstract

The Flash Crash, a brief period of extreme market volatility on May 6, 2010, raised a number of questions about the structure of the U.S. financial markets. In this paper, we describe the market structure of the bellwether E-mini S&P 500 stock index futures market on the day of the Flash Crash. We use audit-trail, transaction-level data for all regular transactions to classify over 15,000 trading accounts that traded on May 6 into six categories: High Frequency Traders, Intermediaries, Fundamental Buyers, Fundamental Sellers, Opportunistic Traders, and Small Traders. We ask three questions. How did High Frequency Traders and other categories trade on May 6? What may have triggered the Flash Crash? What role did High Frequency Traders play in the Flash Crash? We conclude that High Frequency Traders did not trigger the Flash Crash, but their responses to the unusually large selling pressure on that day exacerbated market volatility.

*Andrei Kirilenko is with the Commodity Futures Trading Commission (CFTC), Pete Kyle is with the University of Maryland - College Park and the CFTC Technology Advisory Committee, Mehrdad Samadi is with the CFTC, and Tugkan Tuzun is with the University of Maryland - College Park and the CFTC. We thank Robert Engle and seminar partcipants at the Columbia-NYU Quantitative Finance Seminar, Columbia Conference on Quantitative Trading and Asset Management, the International Association of Financial Engineers, and the University of Maryland. The views expressed in this paper are our own and do not constitute an official position of the Commodity Futures Trading Commission, its Commissioners or staff.

1 Introduction

On May 6, 2010, in the course of about 30 minutes, U.S. stock market indices, stock-index futures, options, and exchange-traded funds experienced a sudden price drop of more than 5 percent, followed by a rapid rebound. This brief period of extreme intraday volatility, commonly referred to as the "Flash Crash", raises a number of questions about the structure and stability of U.S. financial markets.

A survey conducted by Market Strategies International between June 23-29, 2010 reports that over 80 percent of U.S. retail advisors believe that "overreliance on computer systems and high-frequency trading" were the primary contributors to the volatility observed on May 6. Secondary contributors identified by the retail advisors include the use of market and stop-loss orders, a decrease in market maker trading activity, and order routing issues among securities exchanges.

Testifying at a hearing convened on August 11, 2010 by the Commodity Futures Trading Commission (CFTC) and the Securities and Exchange Commission (SEC), representatives of individual investors, asset management companies, and market intermediaries suggested that in the current electronic marketplace, such an event could easily happen again.

In this paper, we describe the market structure of the bellwether E-mini Standard & Poor's (S&P) 500 equity index futures market on the day of the Flash Crash. We use audit-trail, transaction-level data for all regular transactions in the June 2010 E-mini S&P 500 futures contract (E-mini) during May 3-6, 2010 between 8:30 a.m. CT and 3:15 p.m. CT. This contract is traded exclusively on the Chicago Mercantile Exchange (CME) Globex trading platform, a fully electronic limit order market. For each transaction, we use data fields that allow us to identify trading accounts of the buyer and seller; the time, price and quantity of execution; the order and order type, as well as which trading account initiated the transaction.

Based on their trading behavior, we classify each of more than 15,000 trading accounts that participated in transactions on May 6 into one of six categories: High Frequency Traders (HFTs), Intermediaries, Fundamental Buyers, Fundamental Sellers, Opportunistic Traders and Small Traders.

We ask three questions. How did High Frequency Traders and other categories trade on May 6? What may have triggered the Flash Crash? What role did the High Frequency Traders play in the Flash Crash?

We find evidence of a significant increase in the number of contracts sold by Fundamental Sellers during the Flash Crash. Specifically, between 1:32 p.m. and 1:45 p.m. CT–the 13-minute period when prices rapidly declined–Fundamental Sellers were net sellers of more than 80,000 contracts, while Fundamental Buyers were net buyers of only about 50,000 contracts. This level of net selling by Fundamental Sellers is about 15 times larger than their net selling over the same 13-minute interval on the previous three days, while this level of net buying by the Fundamental Buyers is about 10 times larger than their buying over the same time period on the previous three days.

In contrast, between 1:45 p.m. and 2:08 p.m. CT, the 23-minute period of the rapid price rebound of the E-mini — Fundamental Sellers were net sellers of more than 110,000 contracts and Fundamental Buyers were net buyers of more than 110,000 contracts. This level of net selling by Fundamental Sellers is about 10 times larger than their selling during same 23-

minute interval on the previous three days, while this level of buying by the Fundamental Buyers is more than 12 times larger than their buying during the same interval on the previous three days.

We find that on May 6, the 16 trading accounts that we classify as HFTs traded over 1,455,000 contracts, accounting for almost a third of total trading volume on that day. Yet, net holdings of HFTs fluctuated around zero so rapidly that they rarely held more than 3,000 contracts long or short on that day. Because net holdings of the HFTs were so small relative to the selling pressure from the Fundamental Sellers on May 6, the HFTs could not have prevented the fall in prices without dramatically altering their trading strategies.

We also find that HFTs did not change their trading behavior during the Flash Crash. On the three days prior to May 6, on May 6, as well as specifically during the period when the prices are rapidly going down, the HFTs seem to exhibit the same trading behavior. Namely, HFTs aggressively take liquidity from the market when prices were about to change and actively keep inventories near a target inventory level.

During the Flash Crash, the trading behavior of HFTs, appears to have exacerbated the downward move in prices. High Frequency Traders who initially bought contracts from Fundamental Sellers, proceeded to sell contracts and compete for liquidity with Fundamental Sellers. In addition, HFTs appeared to rapidly buy and contracts from one another many times, generating a "hot potato" effect before Fundamental Buyers were attracted by the rapidly falling prices to step in and take these contracts off the market.

We also estimate the market impacts of different categories of traders and find that High Frequency Traders effectively predict and react to price changes. Fundamental Traders do not have a large perceived price impact possibly due to their desire to minimize their price impact and reduce transaction costs.

Nearly 40 years before the Flash Crash, Black (1971) conjectured that irrespective of the method of execution or technological advances in market structure, executions of large orders would always exert an impact on price. Black also conjectured that liquid markets exhibit price continuity only if trading is characterized by large volume coming from small individual trades.

In the aftermath of the Flash Crash, we add to these conjectures that technological innovation and changes in market structure enable trading strategies that, at times, may amplify the price impact of a large order into a market disruption. We believe that technological innovation is essential for market advancement. As markets advance, however, safeguards must be appropriately adjusted to preserve the integrity of financial markets.

The paper proceeds as follows. In Section 2, we review the relevant literature. In Section 3, we summarize the public account of events on May 6, 2010. In Sections 4 and 5 we describe the E-mini S&P 500 futures contract and provide a description of the audit-trail, high frequency data we utilize. In Section 6, we describe our trader classification methodology. In Section 7, we present our analysis of the trading strategies of High Frequency Traders Intermediaries. In Section 8, we describe the behavior of Fundamental Buyers and Sellers. In Section 9, we examine the activity of Opportunistic traders. In Section 10, we present the market impact regressions. In Section 11, we present our interpretation of the Flash Crash. Section 12 concludes the paper.

2 Literature

Nearly 40 years ago, when exchanges first contemplated switching to fully automated trading platforms, Fisher Black surmised that regardless of market structure, liquid markets exhibit price continuity only if trading is characterized by a large volume of small individual trades. Black (1971) also stated that large order executions would always exert an impact on price, irrespective of the method of execution or technological advances in market structure.

At that time, stock market "specialists" were officially designated market makers, obligated to maintain the order book and provide liquidity.[1] In the trading pits of the futures markets, many floor traders were unofficial, but easily identifiable market makers. Trading environments in which market makers are distinct from other traders are examined in the theoretical models of Kyle (1985) and Glosten and Milgrom (1985,1989).

As markets became electronic, a rigid distinction between market makers and other traders became obsolete. Securities exchanges increasingly adopted a limit order market design, in which traders submit orders directly into the exchange's electronic systems, bypassing both designated and unofficial market makers. This occurred because of advances in technology, as well as regulatory requirements. Theoretical models of limit order markets include, among others, Parlour (1998), Foucault (1999), Biais, Martimor and Rochet (2000), Goettler, Parlour, and Rajan (2005, 2009), and Rosu (2009).

As more data became available, empirical research has confirmed a number of empirical regularities related to such issues as multiple characterizations of prices, liquidity, and order flow. Madhavan (2000), Biais, Glosten and Spatt (2002), and Amihud, Mendelson and Pedersen (2005) provide surveys of empirical market microstructure studies.

Most recently, Cespa and Foucault (2008) and Moallemi and Saglam (2010) proposed theoretical models of latency - an increasingly important dimension of electronic trading. As low-latency, electronic limit order markets allowed for the proliferation of algorithmic trading strategies, a number of research studies aimed to examine algorithmic trading. Hendershott et al (2008) and Hendershott and Riordan (2008) examine the impact of algorithmic traders in stock markets and find their presence beneficial.

Another strand of literature examines optimal execution of large orders — a particular form of algorithmic trading strategies designed to minimize price impact and transaction costs. Studies on this issue include Bertsimas and Lo (1998), Almgren and Chriss (1999,2000), Engle and Ferstenberg (2007), Almgren and Lorenz (2006), and Schied and Schnenborn (2007).

Separately, Obizhaeva and Wang (2006) and Alfonsi et al (2008) study optimal execution by modeling the underlying limit order book. Brunnermier and Pedersen (2005), Carlin et al (2007), and Moallemi et al (2009) integrate the presence of an arbitrageur who can "front-run" a trader's execution. The majority of these studies find that it is optimal to split large orders into multiple executions to minimize price impact and transaction costs.

The effects of large trades on a market have also been thoroughly examined empirically by a multitude of authors starting with Kraus and Stoll (1972) who utilized data from the New York Stock Exchange.[2] These studies generally find that the execution of large orders

[1]Large orders were executed "upstairs" by block trading firms.

[2]See, among others, Holthausen et al (1987, 1990), Chan and Lakonishok (1993, 1995), Chiyachantana et al (2004), Keim and Madhavan (1996, 1997), and Berkman (1996).

exerts both permanent and temporary price impact, while reducing market liquidity.

3 Market Events on May 6, 2010: The Flash Crash

On May 6, 2010, major stock indices and stock index products rapidly dropped by more than 5 percent and then quickly recovered. The extreme intraday volatility in stock index prices is presented in Figure 1.

<Insert Figure 1>

Between 13:45 and 13:47 CT, the Dow Jones Industrial Average (DJIA), S&P 500, and NASDAQ 100 all reached their daily minima. During this same period, all 30 DJIA components reached their intraday lows. The DJIA components dropped from -4% to -36% from their opening levels. The DJIA reached its trough at 9,872.57, the S&P 500 at 1,065.79, and the NASDAQ 100 at 1,752.31. The E-mini S&P 500 index futures contract bottomed at 1,056.00.[3]

During a 13 minute period, between 13:32:00 and 13:45:27 CT, the front-month June 2010 E-mini S&P 500 futures contract sold off from 1127.75 to 1,070.00 , (a decline of 57.75 points or 5.1%). At 13:45:27, sustained selling pressure sent the price of the E-mini down to 1062.00. Over the course of the next second, a cascade of executed orders caused the price of the E-mini to drop to 1056.00 or 1.3%. The next executed transaction would have triggered a drop in price of 6.5 index points (or 26 ticks). This triggered the CME Globex's Stop Logic Functionality at 13:45:28. The Stop Logic Functionality pauses executions of all transactions for 5 seconds, if the next transaction were to execute outside the price range of 6 index points either up or down. During the 5-second pause, called the "Reserve State," the market remains open and orders can be submitted, modified or cancelled, however, execution of pending orders are delayed until trading resumes.

At 13:45:33, the E-mini exited the Reserve State and the market resumed trading at 1056.75. Prices fluctuated for the next few seconds. At 13:45:38, price of the E-mini began a rapid ascent, which, while occasionally interrupted, continued until 14:06:00 when the price reached 1123.75, equivalent to a 6.4% increase from that day's low of 1056.00. At this point, the market was practically at the same price level where it was at 13:32:00 when the rapid sell-off began.

Trading volume of the E-mini increased significantly during the period of extreme price volatility. Figure 2 presents trading volume and transaction prices on May 6, 2010 over 1 minute intervals.

<Insert Figure 2>

[3]For an in-depth review of the events of May 6, 2010, see the CFTC-SEC Staff Report entitled "Preliminary Findings Regarding the Market Events of May 6, 2010."

During the period of extreme market volatility, a large sell program was executed in the June 2010 E-mini S&P 500 futures contract. " At 2:32 p.m., against this backdrop of unusually high volatility and thinning liquidity, a large fundamental trader (a mutual fund complex) initiated a sell program to sell a total of 75,000 E-Mini contracts (valued at approximately $4.1 billion) as a hedge to an existing equity position...This large fundamental trader chose to execute this sell program via an automated execution algorithm (Sell Algorithm) that was programmed to feed orders into the June 2010 E-Mini market to target an execution rate set to 9% of the trading volume calculated over the previous minute...The execution of this sell program resulted in the largest net change in daily position of any trader in the E-Mini since the beginning of the year (from January 1, 2010 through May 6, 2010). Only two single-day sell programs of equal or larger size one of which was by the same large fundamental trader were executed in the E-Mini in the 12 months prior to May 6. When executing the previous sell program, this large fundamental trader utilized a combination of manual trading entered over the course of a day and several automated execution algorithms which took into account price, time, and volume. On that occasion it took more than 5 hours for this large trader to execute the first 75,000 contracts of a large sell program." [4]

4 CME's E-mini S&P 500 Equity Index Contract

The CME S&P 500 E-mini futures contract was introduced on September 9, 1997. The E-mini trades exclusively on the CME Globex trading platform in a fully electronic limit order market. Trading takes place 24 hours a day with the exception of short technical break periods. The notional value of one E-mini contract is $50 times the S&P 500 stock index. The tick size for the E-mini is 0.25 index points or $12.50.

The number of outstanding E-mini contracts is created directly by buying and selling interests. There is no limit on how many contracts can be outstanding at any given time. At any point in time, there are a number of outstanding E-mini contracts with different expiration dates. The E-mini expiration months are March, June, September, and December. On any given day, the contract with the nearest expiration date is called the front-month contract. The E-mini is cash-settled against the value of the underlying index and the last trading day is the third Friday of the contract expiration month. Initial margin for speculators and hedgers(members) are $5,625 and $4,500, respectively. Maintenance margins for both speculators and hedgers(members) are $4,500. Empirically, it has been documented that the E-mini futures contract contributes the most to price discovery of the S&P 500 Index.[5]

The CME Globex matching algorithm for the E-mini offers strict price and time priority. Specifically, limit orders that offer more favorable terms of trade (sells at lower prices and buys at higher prices) are executed prior to pre-existing orders. Orders that arrived earlier are executed before other orders at the same price. This market operates under complete price transparency and anonymity. When a trader has his order filled, the identity of his counterparty is not available.

[4] "Findings Regarding the Market Events of May 6, 2010"

[5] See, Hasbrouck (2003).

5 Data

We utilize audit trail, transaction-level data for all outright transactions in the June 2010 E-mini S&P 500 futures contract. These data come from the Computerized Trade Reconstruction (CTR) dataset, which the CME provides to the CFTC. We examine transactions occurring from May 3, 2010 through May 6, 2010, when the markets of the underlying equities of the S&P 500 index are open and before the daily halt in trading, i.e. weekdays between 8:30 a.m. CT and 3:15 p.m. CT. Price discovery typically occurs in the front month contract; the June 2010 contract was the nearby, most actively traded futures contract on May 6.

For each transaction, we use the following data fields: date, time (transactions are recorded by the second), executing trading account, opposite account, buy or sell flag, price, quantity, order ID, order type (market or limit), and aggressiveness indicator (indicates which trader initiated a transaction). These fields allow us to identify two trading accounts for each transaction: a buyer and seller, identify which account initiated a transaction, and whether the parties used market or limit orders to execute the transaction. We can also group multiple executions into an order. Table 1 provides summary of statistics for the June 2010 E-Mini S&P 500 futures contract during May 3-6, 2010.

<Insert Table 1>

According to Table 1, limit orders are the most popular tool for execution in this market. In addition, according to Table 1, trading volume on May 6 was significantly higher compared to the average daily trading volume during the previous three days.

6 Trader Categories

Financial markets are composed of traders that have different holding horizons and trading strategies. Some traders accumulate a position and hold it overnight. Other traders will accumulate a position and offset it within minutes. Yet another group of traders establish and offset a position within a matter of seconds.

Motivated by this and the absence of any designations in the E-mini market, we designate individual trading accounts into six categories based on their trading activity. Our classification method, which is described in detail below, produces the following categories of traders: High Frequency Traders (16 accounts), Intermediaries (179 accounts), Fundamental Buyers (1263), Fundamental Sellers (1276), Opportunistic Traders (5808) and Small Traders (6880).

We define Intermediaries as short horizon investors who follow a strategy of buying and selling a large number of contracts to stay around a relatively low target level of inventory. Specifically, we designate a trading account as an Intermediary if its trading activity satisfies the following two criteria. First, the account's net holdings fluctuate within 1.5% of its end of day level. Second, the account's end of day net position is no more than 5% of its daily trading volume. Together, these two criteria select accounts whose trading strategy is to participate in a large number of transactions, but to rarely accumulate a significant net position.

We define High Frequency Traders as a subset of Intermediaries, who individually participate in a very large number of transactions. Specifically, we order Intermediaries by the number of transactions they participated in during a day (daily trading frequency), and then designate accounts that rank in the top 7% as High Frequency Traders. Once we designate a trading account as a HFT, we remove this account from the Intermediary category to prevent double counting. [6]

We define as Fundamental Traders trading accounts which mostly bought or sold in the same direction during May 6. Specifically, to qualify as a Fundamental Trader, a trading account's end of day net position on May 6 must be no smaller than 15% of its trading volume on that day. This criterion selects accounts that accumulate a significant net position by the end of May 6. Fundamental traders are further separated into Fundamental Buyers and Sellers, depending on whether their end of day net position is positive or negative, respectively. These traders appear to hold their positions for longer periods of time.

We define Small Traders as trading accounts which traded no greater than 9 contracts on May 6.

We classify the remaining trading accounts as Opportunistic Traders. Opportunistic Traders may behave like Intermediaries (both buying and selling around a target net position) and at other times may behave like Fundamental traders (accumulating a directional long or short position).

Figure 3 illustrates the grouping of all trading accounts that transacted on May 6 into six categories of traders. The panels of Figure 3 presents individual trading accounts trading volume (vertical axis) and net position scaled by market trading volume (horizontal axis) for May 3-6.

<Insert Figure 3>

Figure 3 shows that different categories of traders occupy quite distinct, albeit overlapping, positions in the "ecosystem" of a liquid, fully electronic market. HFTs, while very small in number, account for significant portion of trading volume. However, HFTs do not accumulate a large net position. Intermediaries also do not accumulate a large net position but trade much less volume than HFTs. Fundamental Traders accumulate directional positions. Some Fundamental Traders acquire large positions by executing many small-size orders, while others execute fewer large-size orders. Fundamental Traders which accumulate net positions by executing smaller orders may be disguising their trading activity in order to avoid being taken advantage of by the market. Opportunistic Traders at times act like Intermediaries (buying a selling around a given inventory target) and at other times act like Fundamental Traders (accumulating a directional position).

More formally, Table 2 presents descriptive statistics for these categories of traders and the overall market during May 3-5, 2010 and on May 6, 2010.

[6]To account for a possible change in trader behavior on May 6, we classify HFTs and Intermediaries using trading data for May 3-5, 2010. We use data for May 6, 2010 to designate traders into other trading categories.

<Insert Table 2>

In order to characterize market participation of different categories of traders, we compute their shares of total trading volume. Table 2 shows that HFTs account for approximately 34% of total trading volume during May 3-5 and 29% of trading volume on May 6. Intermediaries account for approximately 10.5 % of trading volume during May 3-5 and 9% of trading volume on May 6. Trading volume of Fundamental Buyers and Sellers accounts for about 12% of the total trading volume during May 3-5. On May 6, Fundamental Buyers account for about 12% of total volume, while Fundamental Sellers account for 10% of total volume. We interpret the composition of this market as approximately 20% fundamental demand and 80% intermediation.

In order to further characterize whether categories of traders were primarily takers of liquidity, we compute the ratio of transactions in which they removed liquidity from the market as a share of their transactions.[7] According to Table 2, HFTs and Intermediaries have aggressiveness ratios of 45.68% and 41.62%, respectively. In contrast, Fundamental Buyers and Sellers have aggressiveness ratios of 64.09% and 61.13%, respectively.

This is consistent with a view that HFTs and Intermediaries generally provide liquidity while Fundamental Traders generally take liquidity. The aggressiveness ratio of High Frequency Traders, however, is higher than what a conventional definition of passive liquidity provision would predict.[8]

In order to better characterize the liquidity provision/removal across trader categories, we compute the proportion of each order that was executed aggressively.[9] Table 3 presents the cumulative distribution of ratios of order aggressiveness.

<Insert Table 3>

According to Table 3, the majority of High Frequency Traders' executed orders are entirely passive. Prior to May 6, about 79% of High Frequency Trader and Intermediary orders

[7]When any two orders in this market are matched, the CME Globex platform automatically classifies an order as 'Aggressive' when it is executed against a 'Passive' order that was resting in the limit order book. From a liquidity standpoint, a passive order (either to buy or to sell) has provided visible liquidity to the market and an aggressive order has taken liquidity from the market. Aggressiveness ratio is the ratio of aggressive trade executions to total trade executions. In order to adjust for the trading activity of different categories of traders, the aggressiveness ratio is weighted either by the number of transactions or trading volume.

[8]This finding is consistent with that of Menkveld et al (2009). One possible explanation for the order aggressiveness ratios of HFTs is that some of them may actively engage in "sniping" orders resting in the limit order book. Cvitanic and Kirilenko (2010) model this trading behavior and conclude that under some conditions this trading strategy may have impact on prices. Similarly, Hasbrouck and Saar (2009) provide empirical support for a possibility that some traders may have altered their strategies by actively searching for liquidity rather than passively posting it.

[9]The following example illustrates how we compute the proportion of each order that was executed aggressively. Suppose that a trader submits an executable limit order to buy 10 contracts and this order is immediately executed against a resting sell order of 8 contracts, while the remainder of the buy order rests in the order book until it is executed against a new sell order of 2 contracts. This sequence of executions yields an aggressiveness ratio of 80% for the buy order, 0% for the sell order of 8 contracts, and 100% for the sell order of 2 contracts.

are resting orders. Executable limit orders are approximately 18% of total HFT orders and 20% of orders for Intermediaries.

As expected, Fundamental Traders utilize orders that consume more liquidity than the orders of HFTs and Intermediaries. During May 3-5, executable orders comprise 46% of the Fundamental Buyers' orders and 47% of the Fundamental Sellers' orders. On May 6, Fundamental Sellers use resting orders more often (59%) and executable orders less often (40%), whereas Fundamental Buyers use executable orders more often (63%) and resting orders less often (45%).

Moreover, during May 3-5, the average order size for both Fundamental Buyers and Sellers is approximately the same - about 15 contracts, while on May 6, the average order size of Fundamental Sellers (about 25 contracts) is more than 2.5 times larger than the average order size of Fundamental Sellers (about 9 contracts).

For all trader categories, order size exhibits an inverse U-shaped aggressiveness pattern: smaller orders tend to be either entirely aggressive or entirely passive. In contrast, larger orders result in both passive and aggressive executions. The number of trades per order also follows a similar pattern with larger orders being filled by a greater number of trade executions.

7 High Frequency Traders and Intermediaries

Together HFTs and Intermediaries account for over 40% of the total trading volume. Given that they account for such a significant share of total trading, we find it essential to analyze their trading behavior.

7.1 HFTs and Intermediaries: Net Holdings

Figure 4 presents the net position holdings of High Frequency Traders during May 3-6, 2010.

<Insert Figure 4>

According to Figure 4, HFTs do not accumulate a significant net position and their position tends to quickly revert to a mean of about zero. The net position of the HFTs fluctuates between approximately ±3000 contracts.

Figure 5 presents the net position of the Intermediaries during May 3-6, 2010.

<Insert Figure 5>

According to Figure 5, Intermediaries exhibit trading behavior similar to that of HFTs. They also do not accumulate a significant net position. Compared to the HFTs, the net position of the Intermediaries fluctuates within a more narrow band of ±2000 contracts, and reverts to a lower target level of net holdings at a slower rate.

On May 6, during the initial price decline, HFTs accumulated a net long position, but quickly offset their long inventory (by selling) before the price decline accelerated. Intermediaries appear to accumulate a net long position during the initial decrease in price, but unlike HFTs, Intermediaries did not offset their position as quickly. The decline in the net position of the Intermediaries occurred when the prices begin to rebound.

7.2 HFTs and Intermediaries: Profits and Losses

In addition, we calculate the profits and losses of High Frequency Traders and Intermediaries on a transaction by transaction basis by employing the following formula.

$$PL_y = \sum_{t=0}^{i}[y_{t-1} \times \Delta p_t] \tag{1}$$

Where y_{t-1} represents the net position of a trader at the time of market transaction t and Δp_t represents the change in price since the last transaction in the market. This measure is calculated from the first transaction of our sample where $t = 0$ through the last transaction, i. Our measure of profitability makes the assumption that trading accounts begin the day with no position. In addition, this measure is comprised of both realized gains and unrealized gains.

Figure 6 shows the profits and losses of High Frequency Traders on May 3-6.

<Insert Figure 6>

High Frequency Traders are consistently profitable although they never accumulate a large net position. This does not change on May 6 as they appear to have been even more successful despite the market volatility observed on that day.

Figure 7 shows the profits and losses of Intermediaries on May 3-6.

<Insert Figure 7>

Intermediaries appear to be relatively less profitable than HFTs. During the Flash Crash, Intermediaries also appeared to have incurred significant losses. This consistent with the notion that the relatively slower Intermediaries were run over by the decrease in price.

Overall, HFTs do not accumulate a significant net position and their position tends to quickly revert to a mean of about zero. Combined with their large share of total trading volume (34%), HFTs seem to employ trading strategies to quickly trade through a large number of contracts, without ever accumulating a significant net position. These strategies may be operating at such a high speed, that they do not seem to be affected by the price level or price volatility.

In contrast to HFTs, Intermediaries tend to revert to their target inventory levels more slowly. Because of this, on May 6, Intermediaries may have gotten caught on the wrong side of the market as they bought when prices rapidly fell.

7.3 HFTs and Intermediaries: Net Holdings and Prices

We formally examine the second-by-second trading behavior of HFTs and Intermediaries by examining empirical regularities between their net holdings and prices. Equation 2 presents this in a regression framework.

$$\Delta y_t = \alpha + \phi \Delta y_{t-1} + \delta y_{t-1} + \sum_{i=20}^{0} [\beta_{t-i} \times \Delta p_{t-i}/0.25] + \epsilon_t \qquad (2)$$

where y_t denotes portfolio holdings of HFTs or Intermediaries during second t, where $t = 0$ corresponds to 8:30:00 CT. We utilize the price midpoint of an interval to calculate Price changes, Δp_{t-i}, $i = 0, ..., 20$ are in ticks (0.25 index points) and the change in inventories, Δy_t, is in the number contracts. We interpret δ and ϕ as long-term and short-term mean reversion coefficients.[10]

Table 4 presents estimated coefficients of the regression above. Panels A and B report the results for May 3-5 and May 6, respectively. The t statistics are calculated using the Newey-West (1987) estimator.

<Insert Table 4 >

The first column of Panel A presents regression results for HFTs during May 3-5. The coefficient estimate for the long-term mean reversion parameter is -0.005, and is statistically significant. This suggests that HFTs reduce 0.5% of their position in one second. This long-term mean reversion coefficient corresponds to an estimated half-life of the inventory holding period of 137 seconds. In other words, holding prices constant, HFTs reduce half of their net holdings in 137 seconds. This is significantly smaller than the specialist inventory half-life measures of Hendershott and Menkveld (2010) who employ NYSE dataset from 1994-2005. This may be due to a dramatic increase in speed of intermediation over the last few years. Another explanation may be that this result is due to the fact that market makers are designated in equity markets and we classify our traders with a specific set of criteria. [11]

Changes in net holdings of HFTs are statistically significantly positively related to changes in prices for the contemporaneous price change and the first 4 lags. The estimated coefficients are positive, consistently decaying from the high of 32.089 for the contemporaneous price to the low of 3.909 for the price 4 seconds prior. This can be interpreted as follows: a one tick increase in current price corresponds to a increase of about 32 contracts in the net holdings of HFTs. Moreover, a one tick increase in the current price corresponds to an increase of up to 67 contracts during the next 4 seconds.

In contrast, estimated coefficients for lagged prices 10 to 20 seconds prior to the current holding period are negative and statistically significant. These estimated coefficients fall within a much more narrow range of -2.208 and -5.860. This, in turn, means that a one tick

[10] Dickey-Fuller tests verify that HFT holdings level, Intermediary holdings level, as well as first differences are stationary. This is consistent with the intraday trading practices of HFTs and Intermediaries to target inventory levels close to zero.

[11] We calculate the estimated half-life of the inventory holding period as $\frac{ln(0.5)}{(\delta)}$.

increase in price 10 to 20 seconds before corresponds to a maximum cumulative decrease in net holdings of about 39 contracts.

We interpret these results as follows. HFTs appear to trade in the same direction as the contemporaneous price and prices of the past four seconds. In other words, they buy, if the immediate prices are rising. However, after about ten seconds, they appear to reverse the direction of their trading - they sell, if the prices 10-20 seconds before were rising.

These regression results suggest that, possibly due to their speed advantage or superior ability to predict price changes, HFTs are able to buy right as the prices are about to increase.[12] HFTs then turn around and begin selling 10 to 20 seconds after a price increase.

The second column of Panel A presents regression results for the Intermediaries on May 3-5. Similarly to HFTs, the long term mean reversion coefficient for the Intermediaries is -0.004 and is statistically significant. This suggests that the Intermediaries reduce their net holdings by 0.4% after one second. The half-life of their inventory is 173 seconds.

In marked contrast to HFTs, coefficient estimates for the contemporaneous price and the price one second before are negative (and significant) at -13.540 and -1.218, respectively. However, at prices 3 to 8 seconds prior, the estimated coefficients are positive and significant.

These coefficients could be interpreted as follows. The Intermediaries sell when the immediate prices are rising, and buy if the prices 3-8 seconds before were rising. These regression results suggest that, possibly due to their slower speed or inability to anticipate possible changes in prices, Intermediaries buy when the prices are already falling and sell when the prices are already rising.

Panel B presents the results of equation 2 on May 6. The first column of Panel B shows the results for HFTs. The coefficient for the lagged change in holdings parameter is positive but statistically insignificant at the 5% level. The coefficients for contemporaneous and 1st lagged price changes are positive at 10.808 and 4.625, respectively.

This result may suggest that that on May 6, HFTs repeatedly reversed the direction of their trading (e.g., become contrarian, switching from buying to selling, or otherwise) significantly sooner than during May 3-5.

The second column of Panel B reports the results for the change in holdings of Intermediaries on May 6th. The contemporaneous price change estimate is -8.164. The lagged price change coefficients become positive for the next 3 lagged price changes, decaying from 6.635 to 1.138.

We interpret the difference in results between these two samples to a change in Intermediary behavior during the Flash Crash. This may be due to a reduction in liquidity provision from this trader category during the Flash Crash.

7.4 HFTs and Intermediaries: Liquidity Provision/Removal

We consider Intermediaries and HFTs to be very short term investors. They do not hold positions over long periods of time and revert to their target inventory level quickly. Observed trading activity of HFTs can be separated into three parts. First, HFTs seem to anticipate

[12] We also introduce lead price changes up to 10 seconds in this regression framework. Prior to May 6, lead price change coefficients are positive and significant up to three seconds for HFTs while they are negative and significant for Intermediaries. Results are available upon request.

price changes (in either direction) and trade aggressively to profit from it. Second, HFTs seem to provide liquidity by putting resting orders in the direction of the anticipated the price move. Third, HFTs trade to keep their inventories within a target level. The inventory-management trading objective of HFTs may interact with their price-anticipation objective. In other words, at times, inventory-management considerations of HFTs may lead them to aggressively trade in the same direction as the prices are moving, thus, taking liquidity. At other times, in order to revert to their target inventory levels, HFTs may passively trade against price movements and, thus, provide liquidity.

In order to examine the liquidity providing and taking behavior of HFTs and Intermediaries, we separate their changes in holdings into aggressive changes (those incurred via aggressive acquisitions) and passive changes (those incurred via passive acquisitions). Specifically, when traders submit marketable orders into the order book, they are considered to be aggressive. Conversely, the traders' resting orders being executed by a marketable order result in passive execution.

Table 5 presents the regression results of the two components of change in holdings on lagged inventory, lagged change in holdings and lagged price changes over one second intervals. Panel A and Panel B report the results for May 3-5 and May 6th, respectively.

<Insert Table 5 >

The dependent variable in the first column of Panel A is the aggressive change in holdings of HFTs on May 3-5. The short term and long term mean reversion coefficients are statistically significant, -0.042% and -.005%, respectively. In other words, HFTs aggressively reduce 0.5% of their holdings in one second. The coefficient estimates for price changes are positive for the contemporaneous and first 4 lagged prices, decaying from 57.778 to 3.290. This can be interpreted as follows: a one tick increase in current price corresponds to an aggressive increase of position of about 58 contracts by HFTs. Moreover, a one tick increase in the current price corresponds to an increase of up to 99 contracts during the next 4 seconds.

The second column of Panel A presents the regression results for the passive change in holdings of HFTs on May 3-5. The coefficient for lagged change in holdings is 0.036 and statistically significant. The long term mean reversion estimate is -0.001, which is smaller than the coefficient from the aggressive holdings change regression. The coefficient estimates for the price changes are almost always negative. The contemporaneous and first lagged price changes are negative and statistically significant; ranging from -25.689 for the contemporaneous price change to -5.371 for the 1st lagged price change.

Given the difference in magnitude between the aggressive and passive long term mean reversion coefficients, we interpret these results as follows, HFTs may be reducing their positions and reacting to anticipated price changes by submitting marketable orders. In addition, passive holdings changes of HFTs reflect liquidity provision.

The dependent variable in the third column of Panel A is the aggressive holdings change of the Intermediaries on May 3-5. The coefficients for lagged change in holdings and lagged inventory level are 0.007 and -0.002, respectively. This result corresponds to Intermediaries reducing 0.2% of their holdings aggressively in one second. The coefficients for the current and lagged price changes are positive; decreasing from 6.377 for the current price change to 1.007 for the 10th lagged price change.

These estimates are smaller than the estimates for HFTs. Accordingly, we interpret these results as evidence suggesting that Intermediaries are slower than HFTs in responding to anticipated price changes. [13]

The fourth column of Panel A presents the results for the passive position change component of Intermediaries' activity. The coefficient estimates for lagged change in holdings and lagged level of holding of Intermediaries are -0.013 and -0.002, respectively. These coefficients are similar to those we observe from the passive trading of Intermediaries. The coefficient estimates for price changes are statistically significant and negative through the 3rd lag. The coefficients range from -19.917 for the current price change to -1.117 for the 3rd lagged price change.

Our interpretation of these results suggests that given the similar passive and aggressive mean reversion coefficients, Intermediaries use primarily marketable orders to move to their target inventory level. The passive holdings change for Intermediaries is also contrarian to price fluctuations, suggesting that the passive holdings change can be a good proxy for the liquidity provision of Intermediaries.

In summary, the larger coefficient for the Aggressive long term mean reversion parameter, suggests that HFTs very quickly reduce their inventories by submitting marketable orders. They also aggressively trade when prices are about to change. Over slightly longer time horizons, however, HFTs sometimes act as providers of liquidity.

The first column of Panel B presents the results for aggressive holdings change of HFTs on May 6th. Only the coefficient on the current price change is positive and statistically significant; 23.703. The second column of Panel B shows the results for passive holdings change of HFTs. The contemporaneous price coefficient, -12.895, is statistically significant.

These results are qualitatively similar to those we observe on the 3 days prior to May 6. Therefore, we interpret these results as evidence that HFTs did not significantly alter their behavior during the Flash Crash. However, they may have executed their trading strategies faster as price volatility increased.

The third column of Panel B presents the results for the aggressive positions change of Intermediaries. The contemporaneous price change coefficient is 4.939 and statistically significant. The fourth column in Panel B displays the results for passive holdings change of Intermediaries. The contemporaneous price change coefficient is -13.103 and statistically significant.

The coefficients on price changes for the Intermediary passive holdings change regression are smaller than those we observe prior to May 6th. We interpret this as a possible decrease in liquidity provision by Intermediaries during the Flash Crash.

[13]We also introduce lead price changes up to 10 seconds into this regression framework. Price change coefficients are positive and significant for the aggressive trading of High Frequency Traders before May 6. In addition, the $Adj - R^2$ increases from 0.0427 to 0.0804 for HFTs whereas it does not significantly. We interpret this as evidence that future price changes are valuable when explaining the trading behavior of HFTs as they may be anticipating price changes more effectively than Intermediaries.

7.5 HFTs and Intermediaries: The Flash Crash

To examine these participants' activity at an even higher resolution during the Flash Crash. We employ equation 2 during the 36-minute period of the Flash Crash - starting at 13:32 p.m. and ending at 14:08 p.m. CT. We partition this sample into two sub samples, the price crash (DOWN, 13:32-13:45 p.m. CT) and recovery (UP, 13:45-14:08 CT), presented in Panels A and B, respectively of Table 6.

<Insert Table 6 >

The first column of Panel A presents the results for aggressive holdings change of HFTs on May 6 during the rapid price decline. The long term mean reversion coefficient is -0.008 and statistically insignificant. The contemporaneous price change coefficient is positive and statistically significant at 24.226.

The second column of Panel A presents passive change in holding of HFTs during the price decline. The long term mean reversion coefficient is positive but statistically insignificant. The contemporaneous price coefficient is 8.533 and statistically significant.

We interpret these results as follows: As the price of the E-mini contract declined, High Frequency Traders were the counterparties to Opportunistic Traders' aggressive buying. However, the aggressive buying of Opportunistic Traders did not affect the direction of the price move. In addition, HFTs did not alter their behavior significantly when prices were rapidly going down. The shorter duration of statistical significance on price change coefficients may be a function of the price volatility observed during the Flash Crash.

The third column of Panel A presents the results for Intermediaries' aggressive position change on May 6th during as the price of the E-mini decreased rapidly. Price change coefficients are positive and statistically significant through the 2nd lag, ranging from 8.251 to 4.257.

The fourth column of Panel A presents the results for the passive position changes of Intermediaries during the decrease in price. The long term mean reversion coefficient is -0.012 and statistically significant. The coefficient for the contemporaneous price change is -9.603 and statistically significant.

These findings are not much different from those we obtain in previous regressions. Accordingly we interpret these results as evidence that Intermediaries did not seem to alter their trading strategies significantly as the price of the E-mini contract declined.

The dependent variable in the first column of Panel B is HFTs aggressive position change while the prices are rapidly going up. The long term mean reversion coefficient is -0.005 and statistically significant. The coefficient for the contemporaneous price change is -0.251 and statistically insignificant. These results are quantitatively different than those we observe in previous regressions.

We interpret this lack of statistical significance in the relationship between HFT aggressive net position changes and prices as being related to the increase in market volatility and the influx of Fundamental Buyers who bought as the price of the E-mini contract recovered after the trading pause.

The results in the second column of Panel B present the relation between prices and passive net position changes of HFTs when the prices were on their way up. The long term mean reversion coefficient is again insignificant. The statistically significant contemporaneous price change coefficient, -9.107, is similar to past regressions of passive holdings changes but differs from the result of 8.533 during the price decline.

We interpret these results as a continuation in liquidity provisions by HFTs as the price of the E-mini contract recovered to levels observed before the Flash Crash.

The third column of Panel B presents the regression results for the aggressive position change of Intermediaries. The long term mean reversion coefficient is -0.004 and is statistically significant. Coefficients are statistically significant and positive for the contemporaneous and first lagged price change at 2.912 and 2.150, respectively. This is smaller than the same coefficient during the regression of Intermediary aggressive holdings changes during the crash.

The fourth column of Panel B lists the regression results where the passive position changes of Intermediaries during the price recovery of the E-mini contract. Although the contemporaneous price coefficient is negative and statistically significant, the magnitude of this coefficient, -4.105, is considerably smaller the coefficient observed in the fourth column of Panel A.

We attribute this decrease in magnitude of contemporaneous price change to a decrease in liquidity provision by Intermediaries during this time period. However, the relatively smaller decrease in the aggressive holdings change coefficient compared to that of HFTs may be due to the increase in aggressiveness of Intermediaries who sought to offset their disadvantageous positions during the Flash Crash.

7.6 HFTs and Intermediaries: The Hot Potato Effect

A basic characteristic of futures markets is that they remain in zero net supply throughout the day. In other words, for each additional contract demanded, there is precisely one additional contract supplied. End of day open interest presents a single reading of the levels of supply and demand at the end of that day.

In intraday trading, changes in net demand/supply result from changes in net holdings of different traders within a specified period of time, e.g., one minute. These minute by minute changes in the net positions of individual trading accounts can be aggregated to get a minute by minute net change in holdings for our six trader categories. To change their net position by one contract, a trader may buy one contract or may buy 101 contracts and sell 100 contracts.

We examine the ratio of trading volume during one minute intervals to the change in net position over one minute intervals to study the relationship between High Frequency Trader trading volume and changes in net position. We calculate the same metric for Intermediaries and find that although High Frequency Traders are active before and during the Flash Crash, they do not significantly change their net positions.

We find that compared to the three days prior to May 6, there was an unusually level of HFT "hot potato" trading volume — due to repeated buying and selling of contracts accompanied a relatively small change in net position. The hot potato effect was especially pronounced between 13:45:13 and 13:45:27 CT, when HFTs traded over 27,000 contracts, which accounted for approximately 49% of the total trading volume, while their net position changed by only about 200 contracts.

We interpret this finding as follows: the lack of Opportunistic and Fundamental Traders, as well as Intermediaries, with whom HFTs typically trade just before the E-mini price reached its trough, resulted in higher trading volume among HFTs, creating a hot potato effect. It is possible that during the period of high volatility, Opportunistic and Fundamental Traders were either unable or unwilling to efficiently submit orders. In the absence of their usual trading counterparties, HFTs were left to trade with other HFTs.

8 Fundamental Traders

Trading volume of the Fundamental Buyers and Sellers accounts for about 10-12% of the total trading volume both during May 3-5 and on May 6. However, Fundamental traders typically remove more liquidity from the market than they provide. As a result, a sizable program executed by the Fundamental traders is more likely to have a significant impact on the market.

In this section we examine the trading behavior of Fundamental traders. We ask the following question: Was the trading behavior of Fundamental Buyers and Sellers different on May 6, especially during the period of extreme price volatility?

Table 7 presents the average number of contracts bought and sold by different categories of traders during two time periods on May 3-5 and on May 6. For both May 3-5 and May 6, the period between 1:32 p.m. and 1:45 p.m. CT is defined as 'UP' and the period between 1:45 p.m. and 2:08 p.m. CT is defined as 'DOWN'.

<Insert Table 7 >

According to Table 7, there a significant increase in the number of contracts sold by the Fundamental Sellers during the period of extreme price volatility on May 6 compared to the same period during the previous three days.

Specifically, between 1:32 p.m. and 1:45 p.m. CT, the 13-minute period when the prices rapidly declined, Fundamental Sellers sold more than 80,000 contracts net, while Fundamental Buyers bought approximately 50,000 contracts net. This level of net selling by the Fundamental Sellers is about 15 times larger compared to their net selling over the same 13-minute interval on the previous three days, while the level of net buying by the Fundamental Buyers is about 10 times larger compared to their net buying over the same time period on the previous three days.

In contrast, between 1:45 p.m. and 2:08 p.m. CT, the 23-minute period of the rapid price rebound, Fundamental Sellers sold more than 110,000 contracts net and Fundamental Buyers bought more than 110,000 contracts net. This level of selling by the Fundamental Sellers is about 10 times larger compared than their selling over the same 23-minute interval on the previous three days, while this level of buying by the Fundamental Buyers is more than 12 times larger compared to their buying over the same time period on the previous three days.

In order to visualize the activity of Fundamental and Opportunistic Traders, we calculate the change in net position of these traders during the time surrounding the Flash Crash.

<Insert Figure 8 >

As the price of the E-mini contract decreased, there was also an imbalance in trading activity between Fundamental Buyers and Sellers. Opportunistic Traders appear to have picked up the excess selling pressure. The price of the E-mini contract recovered as Fundamental Buyers entered the market.

9 Opportunistic Traders

Opportunistic Traders comprise approximately a third of trading accounts active on May 6. Accordingly, the trading behavior of Opportunistic Traders, especially during the Flash Crash, warrants discussion. These trading accounts' behavior differs from that of other trader categories.

9.1 Opportunistic Traders: Net Holdings

Opportunistic traders seem to exhibit mean reverting behavior similar to that of HFTs and Intermediaries, but also establish large net positions like Fundamental Traders. Figure 9 illustrates this point by presenting the net holdings of Opportunistic traders on May 3-6.

<Insert Figure 9>

Opportunistic traders increased their net position by approximately 70,000 contracts during the Flash Crash. This buying pressure came at an opportune time as prices had already fallen significantly.

9.2 Opportunistic Traders: Profits and Losses

Figure 10 shows the profits and losses of Opportunistic Traders on May 3-6.

<Insert Figure 10>

The buying activity of Opportunistic Traders during the Flash Crash could have translated into substantial profits as a large portion of their buying was during the price rebound. However, it is important to note the assumptions of this calculation. We assume that traders begin the day with no preexisting position. Accordingly, the massive swings in profits and losses are a function of the large net position Opportunistic Traders established during the Flash Crash.

10 Market Impact

We utilize the Aggressiveness Imbalance indicator to estimate the price impacts of various trader categories. Aggressiveness Imbalance is an indicator designed to capture the direction of the removal of liquidity from the market. Aggressiveness Imbalance is constructed as the difference between aggressive buy transactions minus aggressive sell transactions.

Figure 11 shows the relationship between price and cumulative Aggressiveness Imbalance (aggressive buys - aggressive sells).

<Insert Figure 11>

In addition, we calculate Aggressiveness Imbalance for each category of traders over one minute intervals. For illustrative purposes, the Aggressiveness Imbalance indicator for HFTs and Intermediaries are presented in Figures 12 and 13, respectively.

<Insert Figure 12>

<Insert Figure 13>

According, to Figures 12 and 13, visually, HFTs behave very differently during the Flash Crash compared to the Intermediaries. HFTs aggressively sold on the way down and aggressively bought on the way up. In contrast, Intermediaries are about equally passive and aggressive both down and up.

More formally, we estimate market impact of different categories of traders. The estimates are obtained by running the following minute-by-minute regressions:

$$\frac{\Delta P_t}{P_{t-1} \times \sigma_{t-1}} = \alpha + \sum_{i=1}^{5} [\lambda_i \times \frac{AGG_{i,t}}{Shr_{i,t-1} \times 100,000}] + \epsilon_t \qquad (3)$$

The dependent variable in the regression is the price return scaled by the previous period's volatility.[14] The independent variables in the regression are the aggressiveness imbalance for each trader category scaled by the category's lagged share of market volume times 100,000. The Newey West (1987) estimator t is employed.

Estimated coefficients are presented in Table 8.

<Insert Table 8 >

[14]For the estimate of volatility, we use range - the natural logarithm of the maximum price over the minimum price.

Panel A of Table 8 presents regression results for the period May 3-5. The specification fits quite well with an R^2 of 36% and all estimated price impact coefficients are statistically significant at 5% level.

HFTs and Opportunistic traders have the highest estimated price impact with the coefficients of 5.37 and 7.6, respectively. The estimated price impact of the Intermediaries is the lowest at 0.83. The estimated price impact of the Fundamental Sellers (1.36) is about equal to that of the Fundamental Buyers (1.31).

Panel B of Table 8 presents regression results for May 6. The model seems to have a better fit with an R^2 of 59%. All slope coefficients are again statistically significant at 5% level. The estimated price impact of HFTs is smaller at 3.23. In contrast, the estimates price impact of the Intermediaries (5.99) is more than seven times larger on May 6 compared to the previous three days. The estimated price impact of Opportunistic traders on May 6 (7.49) is about the same as it is during May 3-5. However, the estimated price impact of Fundamental Sellers (0.53) is nearly double that of the Fundamental Buyers (0.53).

We interpret these results as follows. High Frequency Traders have a large, positive coefficient possibly due to their ability to anticipate price changes. In contrast, Fundamental Traders have a much smaller market impact, which is likely due to their explicit trading strategies that try to limit market impact, in order to minimize transaction costs.

To illustrate the fit of these regressions, we use the estimated coefficients from the price impact regression during May 3-5 to fit minute-by-minute price changes on May 6 (Figure 14).

<Insert Figure 14>

According to Figure 14, the fitted price (marked line) is quite close to the actual price (solid line).

11 Discussion: The Flash Crash

We believe that the events on May 6 unfolded as follows. Financial markets, already tense over concerns about the European sovereign debt crisis, opened to news concerning the Greek government's ability to service its sovereign debt. As a result, premiums rose for buying protection against default on sovereign debt securities of Greece and a number of other European countries. In addition, the S&P 500 volatility index ("VIX") increased, and yields of ten-year Treasuries fell as investors engaged in a "flight to quality." By mid-afternoon, the Dow Jones Industrial Average was down about 2.5%.

Sometime after 2:30 p.m., Fundamental Sellers began executing a large sell program. Typically, such a large sell program would not be executed at once, but rather spread out over time, perhaps over hours. The magnitude of the Fundamental Sellers' trading program began to significantly outweigh the ability of Fundamental Buyers to absorb the selling pressure.

HFTs and Intermediaries were the likely buyers of the initial batch of sell orders from Fundamental Sellers, thus accumulating temporary long positions. Thus, during the early moments of this sell program's execution, HFTs and Intermediaries provided liquidity to this sell order.

However, just like market intermediaries in the days of floor trading, HFTs and Intermediaries had no desire to hold their positions over a long time horizon. A few minutes after they bought the first batch of contracts sold by Fundamental Sellers, HFTs aggressively sold contracts to reduce their inventories. As they sold contracts, HFTs were no longer providers of liquidity to the selling program. In fact, HFTs competed for liquidity with the selling program, further amplifying the price impact of this program.

Furthermore, total trading volume and trading volume of HFTs increased significantly minutes before and during the Flash Crash. Finally, as the price of the E-mini rapidly fell and many traders were unwilling or unable to submit orders, HFTs repeatedly bought and sold from one another, generating a "hot-potato" effect.

Yet, Fundamental Buyers, who may have realized significant profits from this large decrease in price, did not seem to be willing or able to provide ample buy-side liquidity. As a result, between 2:45:13 and 2:45:27, prices of the E-mini fell about 1.7%.

At 2:45:28, a 5 second trading pause was automatically activated in the E-mini. Opportunistic and Fundamental Buyers aggressively executed trades which led to a rapid recovery in prices. HFTs continued their strategy of rapidly buying and selling contracts, while about half of the Intermediaries closed their positions and got out of the market.

In light of these events, a few fundamental questions arise. Why did it take so long for Fundamental Buyers to enter the market and why did the price concessions had to be so large? It seems possible that some Fundamental Buyers could not distinguish between macroeconomic fundamentals and market-specific liquidity events. It also seems possible that the opportunistic buyers have already accumulated a significant positive inventory earlier in the day as prices were steadily declining. Furthermore, it is possible that they could not quickly find opportunities to hedge additional positive inventory in other markets which also experienced significant volatility and higher latencies. An examination of these hypotheses requires data from all venues, products, and traders on the day of the Flash Crash.

12 Conclusion

In this paper, we analyze the behavior of High Frequency Traders and other categories of traders during the extremely volatile environment on May 6, 2010.

Based on our analysis, we believe that High Frequency Traders exhibit trading patterns consistent with market making. In doing so, they provide very short term liquidity to traders who demand it. This activity comprises a large percentage of total trading volume, but does not result in a significant accumulation of inventory. As a result, whether under normal market conditions or during periods of high volatility, High Frequency Traders are not willing to accumulate large positions or absorb large losses. Moreover, their contribution to higher trading volumes may be mistaken for liquidity by Fundamental Traders. Finally, when rebalancing their positions, High Frequency Traders may compete for liquidity and amplify price volatility.

Consequently, we believe, that irrespective of technology, markets can become fragile when imbalances arise as a result of large traders seeking to buy or sell quantities larger than intermediaries are willing to temporarily hold, and simultaneously long-term suppliers of liquidity are not forthcoming even if significant price concessions are offered.

We believe that technological innovation is critical for market development. However, as markets change, appropriate safeguards must be implemented to keep pace with trading practices enabled by advances in technology.

References

Alfonsi, A., A. Fruth, and A. Schied, 2008, "Constrained Portfolio Liquidation in a Limit Order Book Model," *Banach Center Publ.* 83, 9–25.

Almgren, R. and N. Chriss, 1999, "Value Under Liquidation," *Risk* 12, 61-63.

Almgren, R. and N. Chriss, 2000, "Execution of Portfolio Transactions," *J. Risk* 3, 5-39.

Almgren, R. and J. Lorenz, 2006, "Bayesian Adaptive Trading With a Daily Cycle," *J. Trading* 1, 38-46.

Amihud, Y., H. Mendelson, and L. Pedersen, 2005, "Liquidity and Asset Prices," *NOW-publishers.com*.

Berkman, H., 1996, "Large Option Trades, Intermediaries and Limit Orders," *Review of Financial Studies* 9, 977–1002.

Bertsimas, D. and A. Lo 1998, "Optimal Control of Execution Costs," *Journal of Financial Markets* 1, 1–50.

Biais, B., L. Glosten, and C. Spatt, 2002, "Market Microstructure: A Survey of Microfoundations, Empirical Results, and Policy Implications," *Journal of Financial Markets* 8, 217–264.

Biais, B., D. Martimort, and J. Rochet, 2000, "Competing Mechanisms in a Common Value Environment," *Econometrica* 68, 799–838.

Black, B., 1971, "Towards a Fully Automated Exchange, Part I," *Financial Analysts Journal* 27, 29-34.

Brunnermeier, M. and L. Pedersen, 2005, "Predatory Trading," *Journal of Finance* 60, 1825-1863.

Carlin, B., M. Lobo, and S. Viswanathan, 2007, "Episodic Liquidity Crises: Cooperative and Predatory Trading," *Journal of Finance* 62, 2235–2274.

Cespa, G. and T. Foucault, 2008, "Insiders-Outsiders, Transparency, and the Value of the Ticker," *Working Paper*.

Chan, L. and J. Lakonishok, 1993, "The Behavior of Stock Prices Around Institutional Trades," *Journal of Financial Economics* 33, 173–200.

Chan, L. and J. Lakonishok, 1995, "Institutional Trades and Intra-Day Stock Price Behavior," *Journal of Finance* 50, 1147–1174.

Chiyachantana, C., P. Jain, C. Jiang, and R. Wood, 2004, "International Evidence on Institutional Trading Behavior and Determinants of Price Impact," *Journal of Finance* 59, 865–894.

Cvitanic, J., and A. Kirilenko, 2010, "High Frequency Traders and Asset Prices," *Working Paper.*

Engle, R. and R. Ferstenberg, 2007, "Execution Risk," *Journal of Portfolio Management*, 33, 34–45.

Foucault, T., 1999, "Order Flow Composition and Trading Costs in a Dynamic Limit Order Market," *Journal of Financial Markets*, 2, 99–134.

Glosten, L. and P. Milgrom, 1985, "Bid, Ask and Transaction Prices in a Specialist Market with Heterogeneously Informed Traders" *Journal of Financial Economics* 14, 71–100.

Glosten, L. and P. Milgrom, 1989, "Insider Trading, Liquidity, and the Role of the Monopolist Specialist" *Journal of Business* 62, 211–236.

Goettler, R., C. Parlour, and U. Rajan, 2005, "Equilibrium in a Dynamic Limit Order Market," *Journal of Finance* 60, 2149–2192.

Goettler, R., C. Parlour, and U. Rajan, 2009, "Informed Traders and Limit Order Markets," *Journal of Financial Economics* 93, 67–87.

Hasbrouck, J., 2003, "Intraday Price Formation in U.S. Equity Index Markets," *Journal of Finance* 58, 2375–2400.

Hasbrouck, J. and G. Saar, 2009, "Technology and Liquidity Provision: The Blurring of Traditional Definitions," *Journal of Financial Markets* 12, 143–172.

Hendershott, T., C. Jones, and A. Menkveld, 2010, "Does Algorithmic Trading Improve Liquidity?" *Journal of Finance* Forthcoming.

Hendershott, T. and A. Menkveld, 2010, "Price Pressures" *Working Paper.*

Hendershott, T. and R. Riordan, 2009, "Algorithmic Trading and Information" *Working Paper.*

Holthausen, R., R Leftwich, and D. Mayers, 1987, "The Effect of Large Block Transactions on Security Prices: A Cross-Sectional Analysis," *Journal of Financial Economics* 19, 43–172.

Holthausen, R., R. Leftwich, and D. Mayers, 1990, "Large-Block Transactions, the Speed of Response, and Temporary and Permanent Stock Price Effects," *Journal of Financial Economics* 26, 71–95.

Keim, D. and A. Madhavan, 1996, “The Upstairs Market for Large-Block Transactions: Analysis and Measurement of Price Effects,” *Review of Financial Studies* 9, 1–36.

Keim, D. and A. Madhavan, 1997, “Transactions Costs and Investment Style: An Inter-Exchange Analysis of Institutional Equity Trades,” *Journal of Financial Economics* 46, 265–292.

Kraus, A. and H. Stoll, 1972, “Price Impacts of Block Trading on the New York Stock Exchange,” *Journal of Finance* 27, 569–588.

Kyle, A., 1985, “Continuous Auctions and Insider Trading,” *Econometrica*, 53, 1315–1335.

Madhavan A., 2000, “Market Microstructure: a Survey,” *Journal of Financial Markets* 3, 205–258.

Menkveld A., A. Sarkar, and M. van der Wel, 2009, “Are Market Makers Uninformed and Passive? Signing Trade in the Absence of Quotes,” *Federal Reserve Bank of New York Staff Reports* 395.

Moallemi C., B. Park, and B. Van Roy, 2009, “Strategic Execution in the Presence of an Uninformed Arbitrageur,” *Working Paper*.

Moallemi C. and M. Saglam, 2010, “The Cost of Latency,” *Working Paper*.

Newey, W. and K. West, 1987, “A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix,” *Econometrica*, 55, 703–765.

Obizhaeva A. and J. Wang, 2006, “Optimal Trading Policy and Demand/ Supply Dynamics,” *Working Paper*.

Parlour, C., 1998, “Price Dynamics in Limit Order Markets” *Review of Financial Studies* 11, 789–816.

Rosu, I., 2009, “A Dynamic Model of the Limit Order Book,” *Review of Financial Studies* 22, 4601–4641.

Schied, A. and T. Schnenborn, 2007, “Optimal Portfolio Liquidation for CARA Investors,” *Working Paper*.

Table 1: Market Descriptive Statistics

	May 3-5	May 6th
Volume	2,397,639	5,094,703
# of Trades	446,340	1,030,204
# of Traders	11,875	15,422
Trade Size	5.41	4.99
Order Size	10.83	9.76
Limit Orders % Volume	95.45%	92.44%
Limit Orders % Trades	94.36%	91.75%
Volatility	1.54%	9.82%
Return	-0.02%	-3.05%

This table presents summary statistics for the June 2010 E-Mini S&P 500 futures contract. The first column presents averages calculated for May 3-5, 2010 between 8:30 and 15:15 CT. The second column presents statistics for May 6t, 2010 between 8:30 to 15:15 CT. Volume is the number of contracts traded. The number of traders is the number of trading accounts that traded at least once during a trading day. Order size and trade sizes are measured in the number of contracts. The use of limit orders are presented both in percent of the number of transactions and trading volume. Volatility is calculated as range, the natural logarithm of maximum price over minimum price within a trading day.

Table 2: Summary Statistics of Trader Categories

Panel A: May 3-5

Trader Type	% Volume	% of Trades	# Traders	Trade Size (Avg.)	Order Size (Avg.)	Limit Orders % Volume	Limit Orders % Trades	Agg Ratio Trade-Weighted	Agg Ratio Vol-Weighted
High Frequency Traders	34.22%	32.56%	15	5.69	14.75	100.000%	100.000%	49.91%	45.68%
Intermediaries	10.49%	11.63%	189	4.88	7.92	99.614%	98.939%	43.10%	41.62%
Fundamental Buyers	11.89%	10.15%	1,013	6.34	14.09	91.258%	91.273%	66.04%	64.09%
Fundamental Sellers	12.11%	10.10%	1,088	6.50	14.20	92.176%	91.360%	62.87%	61.13%
Opportunistic Traders	30.79%	33.34%	3,504	4.98	8.80	92.137%	90.549%	55.98%	54.71%
Small Traders	0.50%	2.22%	6,065	1.22	1.25	70.092%	71.205%	59.04%	59.06%
	Volume	# of Trades	# Traders	Trade Size (Avg.)	Order Size (Avg.)	Limit Orders % Volume	Limit Orders % Trades	Volatility	Return
All	2,397,639	446,340	11,875	5.41	10.83	95.45%	94.36%	1.54%	-0.02%

Panel B: May 6th

Trader Type	% Volume	% of Trades	# Traders	Trade Size (Avg.)	Order Size (Avg.)	Limit Orders % Volume	Limit Orders % Trades	Agg Ratio Trade-Weighted	Agg Ratio Vol-Weighted
High Frequency Traders	28.57%	29.35%	16	4.85	9.86	99.997%	99.997%	50.38%	45.53%
Intermediaries	9.00%	11.48%	179	3.89	5.88	99.639%	99.237%	45.18%	43.55%
Fundamental Buyers	12.01%	11.54%	1,263	5.15	10.43	88.841%	89.589%	64.39%	61.08%
Fundamental Sellers	10.04%	6.95%	1,276	7.19	21.29	89.985%	88.966%	68.42%	65.68%
Opportunistic Traders	40.13%	39.64%	5,808	5.05	10.06	87.385%	85.352%	61.92%	60.28%
Small Traders	0.25%	1.04%	6,880	1.20	1.24	63.609%	64.879%	63.49%	63.53%
	Volume	# of Trades	# Traders	Trade Size (Avg.)	Order Size (Avg.)	Limit Orders % Volume	Limit Orders % Trades	Volatility	Return
All	5,094,703	1,030,204	15,422	4.99	9.76	92.443%	91.750%	9.82%	-3.05%

This table presents summary statistics for trader categories and the overall market. The first column presents statistics prior to May 6 as the average over three trading days, May 3-5, 2010 from 8:30 to 15:15 CT. The second column presents statistics for May 6 from 8:30 to 15:15 CT.

Table 3: Order Properties

Panel A: May 3-5

	Order Aggressiveness Distribution						Avg Order Size						Avg # of Trades Per Order					
	HFT	INT	BUY	SELL	OPP.	SMALL	HFT	INT	BUY	SELL	OPP	SMALL	HFT	INT	BUY	SELL	OPP	SMALL
Agg=0	78.76%	78.61%	53.02%	52.22%	60.43%	43.11%	7.39	6.31	10.25	10.32	6.37	1.20	1.44	1.37	1.51	1.46	1.34	1.01
Agg<=0.1	78.94%	78.66%	53.06%	52.25%	60.47%	43.11%	88.22	52.64	218.07	106.97	239.06	0.00	11.61	8.29	47.71	10.58	40.98	0.00
Agg<=0.2	79.15%	78.72%	53.11%	52.28%	60.51%	43.11%	108.38	50.85	83.64	1089.06	319.81	0.00	14.10	9.67	9.06	195.18	49.90	0.00
Agg<=0.3	79.34%	78.80%	53.17%	52.32%	60.55%	43.11%	133.67	44.87	329.55	353.93	304.87	4.00	18.77	9.26	53.83	35.61	46.19	4.00
Agg<=0.4	79.61%	78.91%	53.23%	52.36%	60.60%	43.11%	103.16	24.16	150.01	474.38	275.38	0.00	16.29	6.31	19.48	61.70	45.78	0.00
Agg<=0.5	80.06%	79.17%	53.38%	52.46%	60.69%	43.11%	94.90	14.93	115.80	112.62	121.34	2.00	14.82	4.40	15.84	14.85	18.26	2.00
Agg<=0.6	80.25%	79.23%	53.43%	52.50%	60.74%	43.11%	219.60	50.06	273.76	344.49	238.27	0.00	35.78	11.07	45.81	54.19	37.54	0.00
Agg<=0.7	80.48%	79.33%	53.52%	52.56%	60.79%	43.11%	196.90	39.42	235.24	314.94	211.10	0.00	32.40	9.97	39.70	50.21	34.11	0.00
Agg<=0.8	80.69%	79.41%	53.58%	52.63%	60.83%	43.11%	252.42	58.44	259.47	242.90	214.29	0.00	43.75	14.29	38.68	37.52	35.43	0.00
Agg<=0.9	80.92%	79.48%	53.67%	52.70%	60.88%	43.11%	241.24	54.55	267.88	311.09	248.32	0.00	42.95	13.72	44.36	49.22	44.28	0.00
Agg<1	81.31%	79.57%	53.73%	52.77%	60.92%	43.11%	230.69	76.02	200.32	293.69	343.05	0.00	42.18	16.10	37.16	44.99	55.80	0.00
Agg<=1	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	25.29	12.62	15.57	15.02	9.64	1.28	4.26	2.30	2.53	2.45	1.99	1.03

Panel B: May 6

	Order Aggressiveness Distribution						Avg Order Size						Avg # of Trades Per Order					
	HFT	INT	BUY	SELL	OPP	SMALL	HFT	INT	BUY	SELL	OPP	SMALL	HFT	INT	BUY	SELL	OPP	SMALL
Agg=0	78.92%	75.47%	44.67%	59.01%	53.95%	38.48%	5.49	5.07	7.72	12.74	7.35	1.17	1.35	1.34	1.38	1.58	1.44	1.01
Agg<=0.1	79.27%	75.58%	44.74%	59.13%	54.03%	38.48%	60.21	30.58	160.02	369.44	208.98	0.00	8.60	5.79	12.05	31.00	28.10	0.00
Agg<=0.2	79.60%	75.72%	44.87%	59.27%	54.15%	38.48%	49.13	18.71	238.71	290.55	191.90	0.00	8.37	4.61	32.89	31.08	35.67	0.00
Agg<=0.3	79.85%	75.85%	44.98%	59.43%	54.23%	38.48%	55.22	12.77	390.79	314.13	150.99	0.00	9.76	4.14	76.69	31.14	23.30	0.00
Agg<=0.4	80.15%	76.18%	45.13%	59.57%	54.34%	38.48%	56.70	12.19	110.54	218.36	105.87	0.00	10.20	3.93	14.36	32.52	16.09	0.00
Agg<=0.5	80.51%	76.81%	45.76%	59.82%	54.48%	38.48%	51.50	5.46	23.85	175.72	78.90	5.00	9.95	2.65	4.65	27.13	13.05	2.00
Agg<=0.6	80.71%	76.92%	45.89%	59.95%	54.57%	38.48%	106.72	18.19	115.93	224.16	155.77	0.00	19.15	5.75	19.48	31.79	25.37	0.00
Agg<=0.7	80.96%	77.10%	46.11%	60.07%	54.65%	38.48%	83.11	13.75	77.65	297.35	169.45	0.00	16.44	4.13	14.43	45.49	28.26	0.00
Agg<=0.8	81.18%	77.26%	46.33%	60.20%	54.76%	38.48%	101.36	16.57	94.00	252.70	139.10	0.00	19.01	5.48	16.28	43.67	27.56	0.00
Agg<=0.9	81.40%	77.35%	46.50%	60.34%	54.83%	38.48%	132.72	29.51	87.68	305.83	175.58	0.00	25.27	8.19	16.04	50.03	32.55	0.00
Agg<1	81.70%	77.40%	46.60%	60.49%	54.90%	38.48%	162.13	43.54	181.96	282.34	219.12	0.00	30.84	10.35	33.11	42.18	40.74	0.00
Agg<=1	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	17.70	7.86	9.28	24.90	10.29	1.28	3.07	1.86	2.01	3.84	2.19	1.04

This table reports order statistics across trader categories. The order aggressiveness is defined as the ratio of size of the aggressive portion of the execution over order size. The order aggressiveness distribution is cumulated over various aggressiveness ratios. Average order size and average number of trades are distributed over various order aggressiveness ratios. Average order size is the average number of contracts traded per order. Average number of trades is the average number of trades an order generates.

Table 4: HFTs and Intermediaries: Net Holdings and Prices

	Panel A: May 3-5			Panel B: May 6	
	Δ NP HFT	**Δ NP INT**		**Δ NP HFT**	**Δ NP INT**
Intercept	-1.637	-0.529	**Intercept**	-3.222	0.038
	(-3.758)	**(-3.632)**		**(-3.429)**	(0.138)
$\Delta NPHFT_{t-1}$	-0.006		$\Delta NPHFT_{t-1}$	0.011	
	(-0.735)			(1.248)	
$NPHFT_{t-1}$	-0.005		$NPHFT_{t-1}$	-0.005	
	(-11.505)			**(-7.229)**	
$\Delta NPINT_{t-1}$		-0.006	$\Delta NPINT_{t-1}$		-0.035
		(-0.673)			**(-2.570)**
$NPINT_{t-1}$		-0.004	$NPINT_{t-1}$		-0.008
		(-10.043)			**(-8.426)**
ΔP_t	32.089	-13.540	ΔP_t	10.808	-8.164
	(18.380)	**(-21.992)**		**(5.142)**	**(-7.274)**
ΔP_{t-1}	17.178	-1.218	ΔP_{t-1}	4.625	6.635
	(12.983)	**(-2.708)**		**(3.639)**	**(9.784)**
ΔP_{t-2}	8.357	2.160	ΔP_{t-2}	-1.520	2.734
	(7.376)	**(5.107)**		(-1.384)	**(4.433)**
ΔP_{t-3}	5.086	2.525	ΔP_{t-3}	-1.360	1.138
	(4.998)	**(6.013)**		(-0.978)	**(3.031)**
ΔP_{t-4}	3.909	2.654	ΔP_{t-4}	-1.815	0.487
	(3.656)	**(6.583)**		(-1.680)	(1.270)
ΔP_{t-5}	1.807	2.499	ΔP_{t-5}	-0.228	-0.768
	(1.578)	**(5.898)**		(-1.680)	(-1.857)
ΔP_{t-6}	-0.078	2.163	ΔP_{t-6}	-0.312	-0.312
	(-0.072)	**(5.448)**		(-0.223)	(-0.826)
ΔP_{t-7}	-1.002	1.842	ΔP_{t-7}	-5.037	-0.617
	(-0.975)	**(4.969)**		**(-3.555)**	(-1.257)
ΔP_{t-8}	-1.756	1.466	ΔP_{t-8}	-1.775	-0.359
	(-1.535)	**(3.901)**		(-1.319)	(-1.044)
ΔP_{t-9}	-1.811	0.453	ΔP_{t-9}	-1.678	-1.105
	(-1.672)	(1.252)		(-1.432)	**(-2.736)**
ΔP_{t-10}	-3.899	0.525	ΔP_{t-10}	-1.654	-0.387
	(-3.795)	(1.366)		(-1.188)	(-0.936)
ΔP_{t-11}	-4.728	-0.026	ΔP_{t-11}	-1.076	-0.628
	(-4.752)	(-0.071)		(-0.903)	(-1.221)
ΔP_{t-12}	-3.456	0.152	ΔP_{t-12}	0.706	-1.171
	(-3.321)	(0.431)		(0.477)	**(-2.163)**
ΔP_{t-13}	-3.799	0.267	ΔP_{t-13}	2.261	-0.617
	(-3.772)	(0.738)		(1.354)	(-1.457)
ΔP_{t-14}	-4.769	0.317	ΔP_{t-14}	-2.664	-0.270
	(-4.708)	(0.822)		**(-2.346)**	(-0.735)
ΔP_{t-15}	-2.735	-0.195	ΔP_{t-15}	0.428	-0.833
	(-2.613)	(-0.544)		(0.330)	**(-2.442)**
ΔP_{t-16}	-2.208	-0.642	ΔP_{t-16}	-0.683	0.227
	(-2.123)	(-1.830)		(-0.385)	(0.638)
ΔP_{t-17}	-2.517	-0.100	ΔP_{t-17}	-0.657	0.293
	(-2.522)	(-0.261)		(-0.469)	(0.783)
ΔP_{t-18}	-4.358	0.044	ΔP_{t-18}	0.446	-0.769
	(-3.989)	(0.117)		(0.264)	**(-2.124)**
ΔP_{t-19}	-4.215	0.568	ΔP_{t-19}	-2.629	-0.296
	(-4.090)	(1.530)		**(-2.072)**	(-0.793)
ΔP_{t-20}	-5.860	-0.120	ΔP_{t-20}	-1.073	-0.706
	(-5.987)	(-0.343)		(-0.781)	(-1.576)
#obs	72837	72837	**#obs**	24275	24275
$Adj-R^2$	0.0194	0.0263	$Adj-R^2$	0.0101	0.0390

This table displays estimated coefficients of the following regression: $\Delta y_t = \alpha + \phi \Delta y_{t-1} + \delta y_{t-1} + \sum_{i=20}^{0} [\beta_{t-i} \times \Delta p_{t-i}/0.25] + \epsilon_t$. The dependent variable is changes in holdings of High Frequency Traders and Intermediaries, respectively. Both changes in holdings, Δy_t, and lagged holdings, $y_t - 1$, are in the number of contracts. Price changes, $\Delta p_t - i$, are in ticks. Estimates are computed for second-by-second observations. The t statistics are calculated using the Newey-West (1987) estimator. t values reported in parentheses are in bold if the coefficients are statistically significant at the 5% level.

Table 5: HFTs and Intermediaries: Liquidity Provision/Removal

	Panel A: May 3-5				**Panel B: May 6**			
	Δ A HFT	**Δ P HFT**	**Δ A INT**	**Δ P INT**	**Δ A HFT**	**Δ P HFT**	**Δ A INT**	**Δ P INT**
Intercept	-1.285	-0.352	-0.344	-0.185	-2.863	-0.359	-0.246	0.284
	(-2.855)	(-1.291)	**(-3.040)**	(-1.515)	**(-3.242)**	(-0.670)	(-1.277)	(1.212)
$\Delta NPHFT_{t-1}$	-0.042	0.036			-0.003	0.014		
	(-4.931)	**(6.805)**			(-0.286)	(1.770)		
$NPHFT_{t-1}$	-0.005	-0.001			-0.004	-0.001		
	(-9.619)	**(-3.204)**			**(-5.701)**	**(-2.924)**		
$\Delta NPINT_{t-1}$			0.007	-0.013			-0.003	-0.032
			(1.623)	(-1.683)			(-0.531)	**(-2.557)**
$NPINT_{t-1}$			-0.002	-0.002			-0.003	-0.004
			(-6.150)	**(-6.182)**			**(-4.540)**	**(-4.824)**
ΔP_t	57.778	-25.689	6.377	-19.917	23.703	-12.895	4.939	-13.103
	(29.925)	**(-28.850)**	**(17.751)**	**(-32.937)**	**(7.411)**	**(-5.281)**	**(7.807)**	**(-8.502)**
ΔP_{t-1}	22.549	-5.371	5.791	-7.009	-1.118	5.744	3.909	2.726
	(16.181)	**(-7.829)**	**(17.521)**	**(-18.574)**	(-0.946)	**(4.171)**	**(9.102)**	**(5.343)**
ΔP_{t-2}	9.614	-1.258	4.752	-2.592	-2.661	1.141	1.659	1.075
	(8.089)	(-1.826)	**(15.125)**	**(-7.739)**	**(-2.613)**	(1.101)	**(5.187)**	**(2.279)**
ΔP_{t-3}	5.442	-0.356	3.642	-1.117	-1.151	-0.209	0.536	0.602
	(5.142)	(-0.586)	**(12.586)**	**(-3.383)**	(-0.890)	(-0.175)	**(2.288)**	(1.675)
ΔP_{t-4}	3.290	0.619	3.114	-0.460	-2.814	0.999	0.229	0.258
	(2.937)	(0.949)	**(10.888)**	(-1.366)	**(-2.739)**	(0.994)	(1.004)	(0.690)
ΔP_{t-5}	1.926	-0.119	2.591	-0.092	-0.690	0.461	0.161	-0.929
	(1.664)	(-0.170)	**(8.656)**	(-0.266)	(-0.556)	(0.489)	(0.546)	(-1.822)
ΔP_{t-6}	-0.987	0.909	2.038	0.125	-1.824	1.512	0.053	-0.365
	(-0.872)	(1.374)	**(7.017)**	(0.373)	(-1.475)	(1.344)	(0.210)	(-1.058)
ΔP_{t-7}	-0.291	-0.711	2.101	-0.258	-2.688	-2.350	-0.516	-0.102
	(-0.257)	(-1.065)	**(8.333)**	(-0.812)	**(-2.295)**	(-1.754)	**(-2.345)**	(-0.244)
ΔP_{t-8}	-0.977	-0.779	1.740	-0.274	-2.216	0.441	-0.625	0.267
	(-0.797)	(-1.159)	**(6.540)**	(-0.850)	(-1.910)	(0.394)	**(-2.668)**	(0.815)
ΔP_{t-9}	-0.732	-1.078	1.158	-0.705	-0.801	-0.877	-0.099	-1.007
	(-0.643)	(-1.697)	**(4.541)**	**(-2.259)**	(-0.732)	(-0.896)	(-0.364)	**(-2.525)**
ΔP_{t-10}	-2.543	-1.356	1.007	-0.483	-2.958	1.304	-0.513	0.125
	(-2.370)	**(-2.246)**	**(3.858)**	(-1.538)	**(-2.519)**	(1.253)	(-1.949)	(0.291)
ΔP_{t-11}	-3.536	-1.193	0.425	-0.451	-1.099	0.023	-0.867	0.239
	(-3.356)	**(-1.963)**	(1.612)	(-1.463)	(-1.090)	(0.024)	**(-3.152)**	(0.509)
ΔP_{t-12}	-2.523	-0.934	0.207	-0.054	0.974	-0.268	-0.396	-0.775
	(-2.328)	(-1.436)	(0.781)	(-0.178)	(0.878)	(-0.203)	(-1.514)	(-1.532)
ΔP_{t-13}	-2.130	-1.669	0.502	-0.235	1.169	1.093	-0.293	-0.324
	(-2.040)	**(-2.712)**	(1.868)	(-0.786)	(0.904)	(0.716)	(-1.181)	(-0.838)
ΔP_{t-14}	-4.387	-0.382	0.107	0.210	-1.249	-1.415	-0.450	0.180
	(-4.154)	(-0.631)	(0.396)	(0.630)	(-1.223)	(-1.253)	(-1.892)	(0.522)
ΔP_{t-15}	-1.965	-0.770	0.099	-0.294	1.006	-0.579	-0.535	-0.298
	(-1.834)	(-1.231)	(0.368)	(-0.934)	(0.922)	(-0.638)	**(-2.153)**	(-0.857)
ΔP_{t-16}	-2.434	0.226	-0.182	-0.460	-1.300	0.617	0.215	0.012
	(-2.190)	(0.391)	(-0.673)	(-1.528)	(-1.028)	(0.560)	(0.859)	(0.037)
ΔP_{t-17}	-2.185	-0.332	0.238	-0.338	-1.707	1.051	-0.239	0.532
	(-2.019)	(-0.545)	(0.884)	(-1.066)	(-1.521)	(0.948)	(-0.957)	(1.595)
ΔP_{t-18}	-3.259	-1.099	0.311	-0.267	0.482	-0.036	0.051	-0.820
	(-2.862)	(-1.739)	(1.255)	(-0.824)	(0.440)	(-0.035)	(0.229)	**(-2.537)**
ΔP_{t-19}	-3.585	-0.631	0.544	0.024	-0.746	-1.883	-0.265	-0.0311
	(-3.297)	(-1.014)	**(2.085)**	(0.077)	(-0.761)	(-1.542)	(-1.070)	(-0.0782)
ΔP_{t-20}	-4.621	-1.240	0.211	-0.331	-0.535	-0.538	-0.501	-0.205
	(-4.493)	**(-2.144)**	(0.863)	(-1.114)	(-0.521)	(-0.570)	**(-2.276)**	(-0.484)
#obs	72837	72837	72837	72837	24275	24275	24275	24275
$Adj-R^2$	0.0427	0.0260	0.0202	0.0631	0.0252	0.0270	0.0457	0.0698

This table presents estimated coefficients of the following regression: $\Delta y_t = \alpha + \phi \Delta y_{t-1} + \delta y_{t-1} + \sum_{i=20}^{0} [\beta_{t-i} \times \Delta p_{t-i}/0.25] + \epsilon_t$. Dependent variables are changes in Aggressive and Passive holdings of High Frequency Traders and Intermediaries. Changes in holdings, Δy_t, and lagged holdings, $y_t - 1$, are in the number of contracts. Price changes, $\Delta p_t - i$, are in ticks. Estimates are computed for second-by-second observations. The t statistics are calculated using the Newey-West (1987) estimator. t values reported in parentheses are in bold if the coefficients are statistically significant at the 5% level.

Table 6: Aggressive and Passive Holdings: Flash Crash

	Panel A: Down				Panel B: Up			
	Δ A HFT	**Δ P HFT**	**Δ A INT**	**Δ P INT**	**Δ A HFT**	**Δ P HFT**	**Δ A INT**	**Δ P INT**
Intercept	-0.614	7.792	-1.320	9.992	2.111	-1.880	1.484	-1.477
	(-0.080)	**(2.306)**	(-0.440)	**(3.291)**	(0.676)	(-0.647)	(1.319)	(-1.837)
$\Delta NPHFT_{t-1}$	-0.023	-0.014			0.025	-0.026		
	(-0.748)	(-0.744)			(0.996)	(-1.130)		
$NPHFT_{t-1}$	-0.008	0.0010			-0.005	-0.001		
	(-1.947)	(0.370)			**(-2.258)**	(-0.336)		
$\Delta NPINT_{t-1}$			-0.043	-0.005			0.053	0.008
			(-1.585)	(-0.133)			**(2.563)**	(0.426)
$NPINT_{t-1}$			-0.0003	-0.012			-0.004	-0.0009
			(-0.079)	**(-2.812)**			**(-2.366)**	(-0.654)
ΔP_t	24.226	8.533	8.251	-9.603	-0.251	-9.107	2.912	-4.105
	(2.833)	(1.275)	**(3.864)**	**(-2.618)**	(-0.142)	**(-4.378)**	**(4.257)**	**(-6.296)**
ΔP_{t-1}	2.397	9.540	8.821	2.075	-0.993	6.350	2.150	2.934
	(0.557)	(1.710)	**(6.132)**	(0.977)	(-0.621)	**(2.773)**	**(4.446)**	**(5.790)**
ΔP_{t-2}	-4.273	3.669	4.257	0.298	-3.043	-0.445	0.402	0.457
	(-0.915)	(0.839)	**(2.307)**	(0.214)	**(-1.937)**	(-0.222)	(1.039)	(0.893)
ΔP_{t-3}	-2.891	1.747	0.759	-0.138	0.814	-1.763	-0.099	0.283
	(-0.681)	(0.569)	(0.865)	(-0.130)	(0.392)	(-0.686)	(-0.330)	(0.610)
ΔP_{t-4}	-2.040	-5.780	-2.175	0.009	-2.391	3.192	0.109	0.128
	(-0.510)	**(-2.053)**	**(-2.012)**	(0.007)	(-1.769)	**(2.022)**	(0.386)	(0.316)
ΔP_{t-5}	-4.990	-5.326	0.070	-1.314	0.586	1.898	0.007	-0.657
	(-1.046)	(-0.911)	(0.060)	(-1.302)	(0.403)	(1.088)	(0.019)	(-1.350)
ΔP_{t-6}	-7.924	6.621	-1.187	0.266	-0.426	2.800	0.282	-0.749
	(-1.847)	**(1.994)**	(-1.206)	(0.228)	(-0.345)	(1.515)	(0.873)	(-1.676)
ΔP_{t-7}	6.843	-11.357	0.597	-1.384	-4.091	-3.299	-0.708	-0.753
	(1.651)	**(-2.454)**	(0.640)	(-1.266)	**(-2.690)**	(-1.401)	**(-2.157)**	(-1.605)
ΔP_{t-8}	-6.903	6.837	-2.720	1.184	-0.049	-0.676	-0.401	0.183
	(-1.542)	(1.562)	**(-2.498)**	(0.892)	(-0.032)	(-0.365)	(-1.205)	(0.529)
ΔP_{t-9}	0.624	-7.531	-1.732	-0.761	0.219	-0.115	-0.444	-0.709
	(0.128)	(-1.623)	(-1.385)	(-0.646)	(0.189)	(-0.082)	(-1.244)	(-1.899)
ΔP_{t-10}	2.024	-3.278	-2.189	-0.300	-1.380	0.609	-0.299	-0.302
	(0.324)	(-0.583)	(-1.611)	(-0.194)	(-0.920)	(0.291)	(-0.962)	(-0.778)
ΔP_{t-11}	0.412	4.367	-5.216	-1.190	-0.157	1.102	-0.607	0.200
	(0.068)	(1.076)	**(-4.948)**	(-0.739)	(-0.135)	(0.607)	(-1.593)	(0.449)
ΔP_{t-12}	1.442	2.883	-2.684	1.850	0.700	-0.379	0.092	-0.986
	(0.220)	(0.577)	**(-1.984)**	(1.479)	(0.527)	(-0.163)	(0.288)	**(-2.480)**
ΔP_{t-13}	17.340	-9.284	-0.385	-4.370	2.551	3.614	-0.212	0.429
	(3.049)	(-1.613)	(-0.221)	**(-2.344)**	(1.351)	(1.418)	(-0.643)	(1.027)
ΔP_{t-14}	-11.389	-1.530	-1.904	2.974	0.378	-3.094	0.036	-0.349
	(-2.531)	(-0.226)	(-1.627)	(1.775)	(0.304)	(-1.571)	(0.108)	(-1.080)
ΔP_{t-15}	8.706	-2.304	-4.375	-1.206	1.317	-1.904	-0.297	0.043
	(1.281)	(-0.332)	**(-4.377)**	(-0.783)	(0.862)	(-1.287)	(-0.791)	(0.100)
ΔP_{t-16}	-3.908	-1.352	2.906	0.625	-1.480	0.541	0.372	0.234
	(-0.642)	(-0.229)	(2.064)	(0.369)	(-0.903)	(0.261)	(1.036)	(0.682)
ΔP_{t-17}	6.351	-2.788	-0.147	-1.420	0.765	1.750	-0.241	0.725
	(1.055)	(-0.652)	(-0.096)	(-0.915)	(0.505)	(0.921)	(-0.589)	(1.792)
ΔP_{t-18}	-8.521	-3.988	0.475	0.578	0.675	2.813	0.084	-0.584
	(-1.642)	(-0.647)	(0.375)	(0.356)	(0.452)	(1.533)	(0.252)	(-1.695)
ΔP_{t-19}	6.899	-11.448	1.279	-3.649	-1.076	-3.171	-0.098	-0.086
	(0.990)	**(-2.068)**	(0.936)	(-1.830)	(-0.835)	(-1.773)	(-0.300)	(-0.195)
ΔP_{t-20}	-14.611	6.997	-1.574	4.375	0.945	-1.366	-0.488	0.102
	(-3.011)	(1.226)	(-1.404)	**(2.650)**	(0.678)	(-0.922)	(-1.486)	(0.194)
#obs	808	808	808	808	1347	1347	1347	1347
$Adj-R^2$	0.0423	0.0593	0.1779	0.0739	0.0084	0.0583	0.0655	0.0816

This table displays the results of the regression of $\Delta y_t = \alpha + \phi\Delta y_{t-1} + \delta y_{t-1} + \sum_{i=0}^{20}[\beta_{t-i} \times \Delta p_{t-i}/0.25] + \epsilon_t$ over one second intervals. The dependent variables are aggressive and passive holdings changes of High Frequency Traders and Intermediaries. Changes in holdings (Δy_t) and lagged holdings($y_t - 1$) are defined in contracts. The price changes ($\Delta p_t - i$) are defined in ticks. DOWN period is defined as the interval between 13:32:00 (CT) and 13:45:28 (CT). UP period is defined as the interval between 13:45:33 (CT) and 14:08:00 (CT). The t statistics are calculated using the Newey-West (1987) estimator. t values reported in parentheses are in bold if the coefficients are statistically significant at 5% level.

Table 7: Trading Volume During the Flash Crash

	Panel A: May 3-5			
	DOWN		UP	
	Sell	Buy	Sell	Buy
High Frequency Traders	23,746	23,791	40,524	40,021
Intermediaries	6,484	6,328	11,469	11,468
Fundamental Buyers	3,064	7,958	6,127	14,910
Fundamental Sellers	8,428	3,118	15,855	5,282
Opportunistic Traders	20,049	20,552	37,317	39,535
Small Traders	232	256	428	504
	Panel B: May 6th			
	DOWN		UP	
	Sell	Buy	Sell	Buy
High Frequency Traders	152,436	153,804	191,490	189,013
Intermediaries	32,489	33,694	47,348	45,782
Fundamental Buyers	28,694	78,359	55,243	165,612
Fundamental Sellers	94,101	10,502	145,396	35,219
Opportunistic Traders	189,790	221,236	302,417	306,326
Small Traders	1,032	947	1,531	1,473

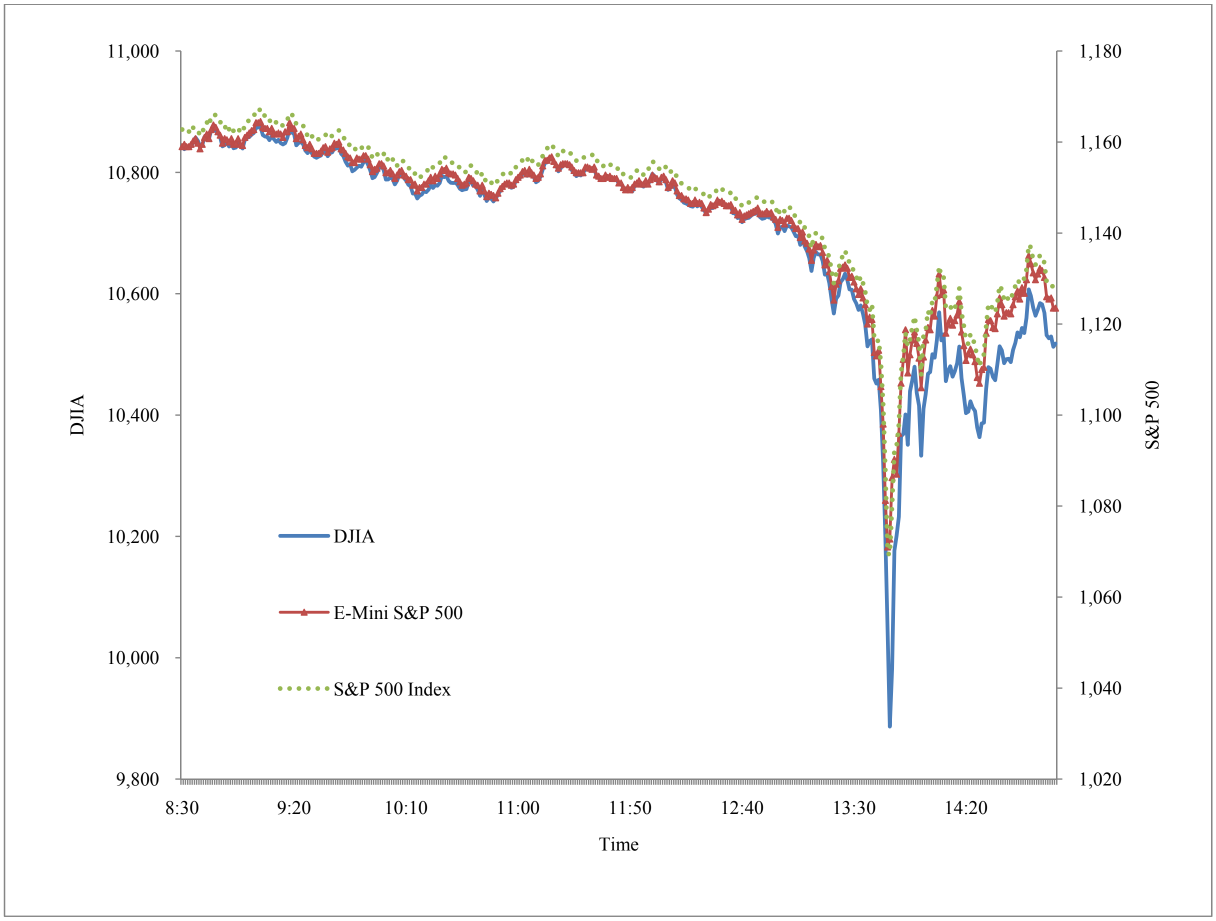
This table presents the number of contracts sold and bought by trader categories during DOWN and UP periods. DOWN period is defined as the interval between 13:32:00 and 13:45:28 CT. UP period is defined as the interval between 13:45:33 and 14:08:00 CT. Panel A reports the average number of contracts bought and sold between May 3 and May 5, 2010 during the DOWN and UP periods in the day. Panel B reports the number of contracts bought and sold on May 6, 2010 during the DOWN and UP periods.

Table 8: Price Impact

	May 3-5	May 6
Intercept	-0.01	0.01
	(-0.19)	(0.31)
High Frequency Traders	5.37	3.23
	(6.43)	**(3.37)**
Intermediaries	0.83	5.99
	(1.08)	**(5.08)**
Fundamental Buyers	1.31	0.53
	(4.32)	**(2.20)**
Fundamental Sellers	1.36	0.92
	(5.81)	**(6.40)**
Opportunistic Traders	7.60	7.49
	(9.74)	**(10.61)**
# of Obs	1210	404
Adj-R2	0.36	0.59

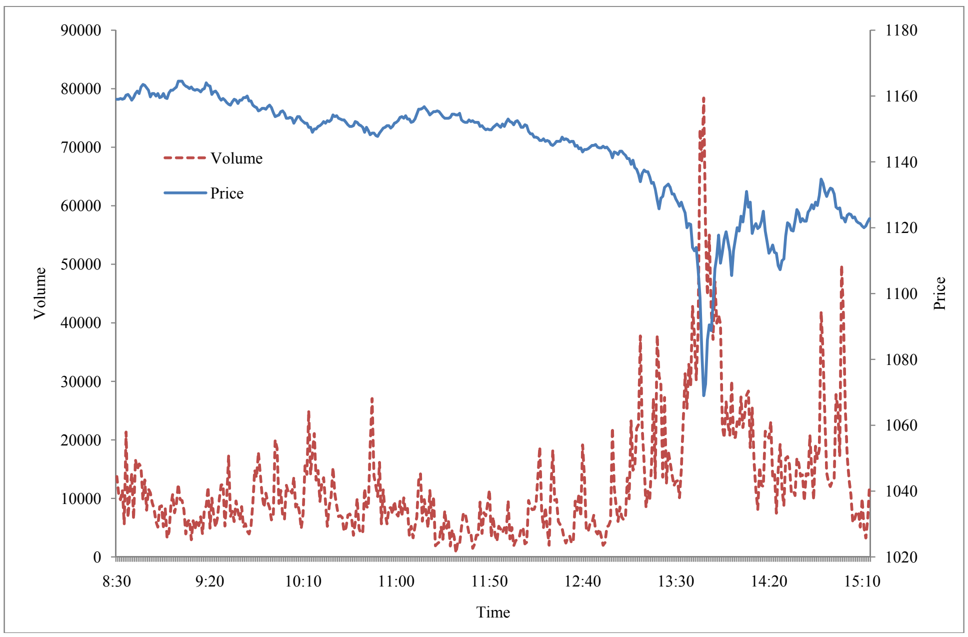
This table presents estimated coefficients of the following regression: $\frac{\Delta P_t}{P_{t-1}\times\sigma_{t-1}} = \alpha + \sum_{i=1}^{5}[\lambda_i \times \frac{AGG_{i,t}}{Shr_{i,t-1}\times 100{,}000}] + \epsilon_t$. The dependent variable is the return scaled by volatility over one minute interval. Independent variables are the aggressiveness imbalances of trader categories scaled by their market share times 100,000. t-values are corrected for serial correlation, up to three lags, using the Newey-West (1987) estimator. t-values, reported in parentheses, are in bold if the coefficients are statistically significant at the 5% level.

Figure 1: U. S. Equity Indices on May 6, 2010



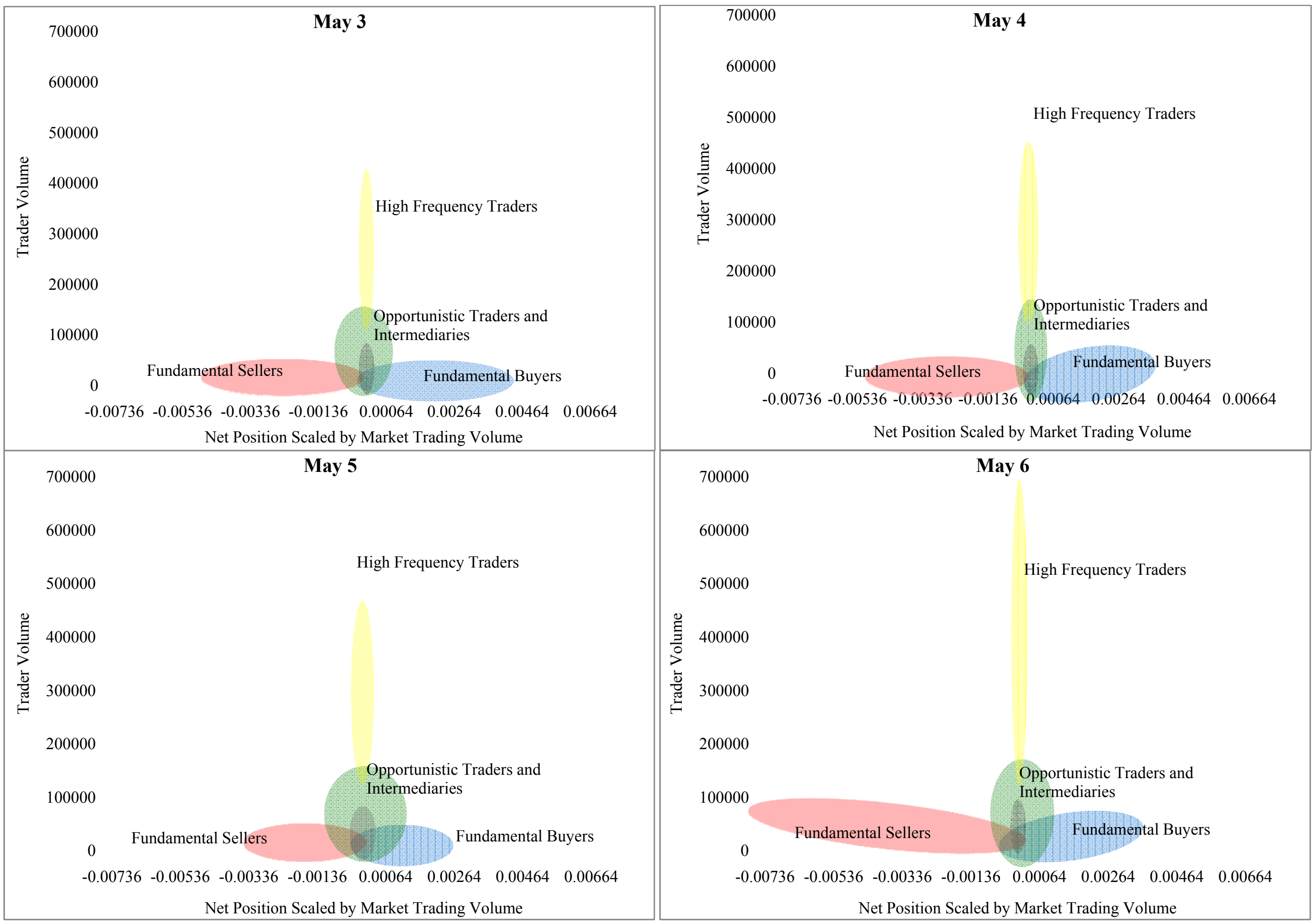
This figure presents end-of-minute transaction prices of the Dow Jones Industrial Average (DJIA), S&P 500 Index, and the June 2010 E-Mini S&P 500 futures contract on May 6, 2010 between 8:30 and 15:15 CT.

Figure 2: Prices and Trading Volume of the E-Mini S&P 500 Stock Index Futures Contract



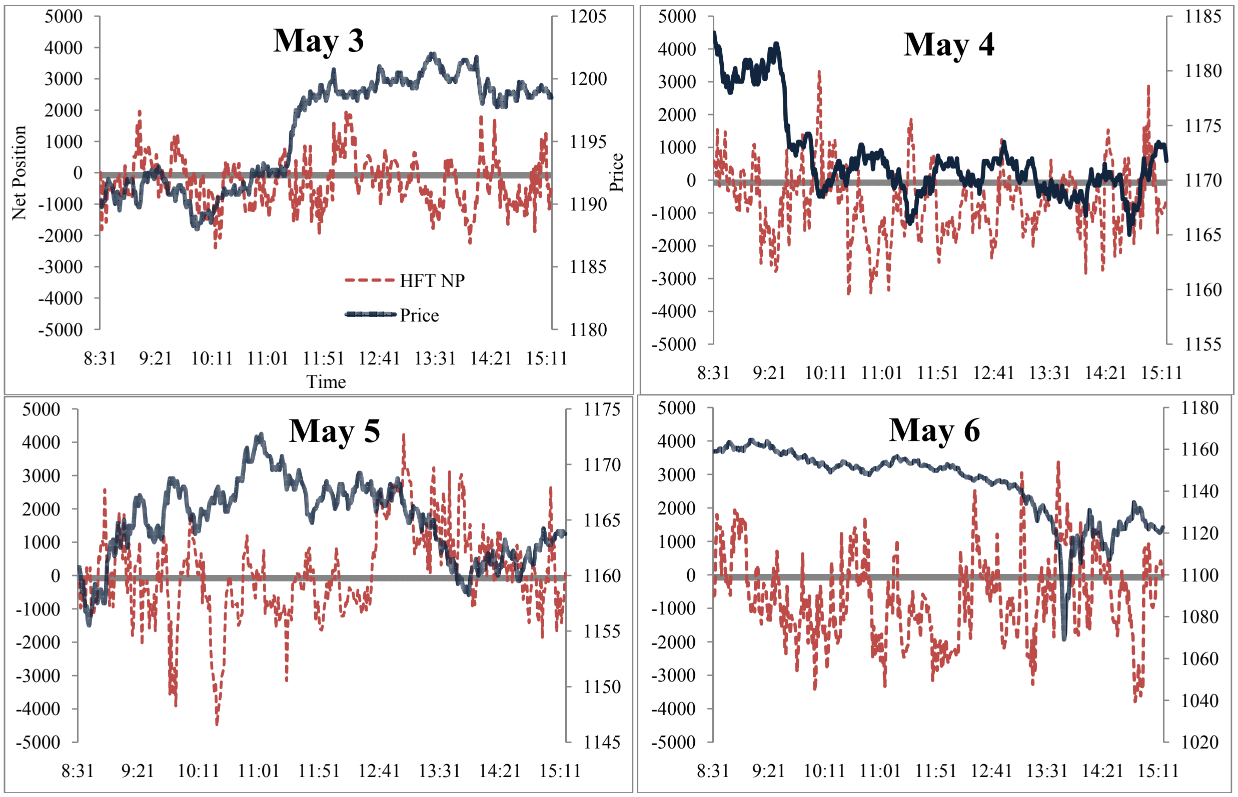
This figure presents minute-by-minute transaction prices and trading volume of the June 2010 E-Mini S&P futures contract on May 6, 2010 between 8:30 and 15:15 CT. Trading volume is calculated as the number of contracts traded during each minute. Transaction price is the last transaction price of each minute.

Figure 3: Trading Accounts Trading Volume and Net Position Scaled by Market Trading Volume



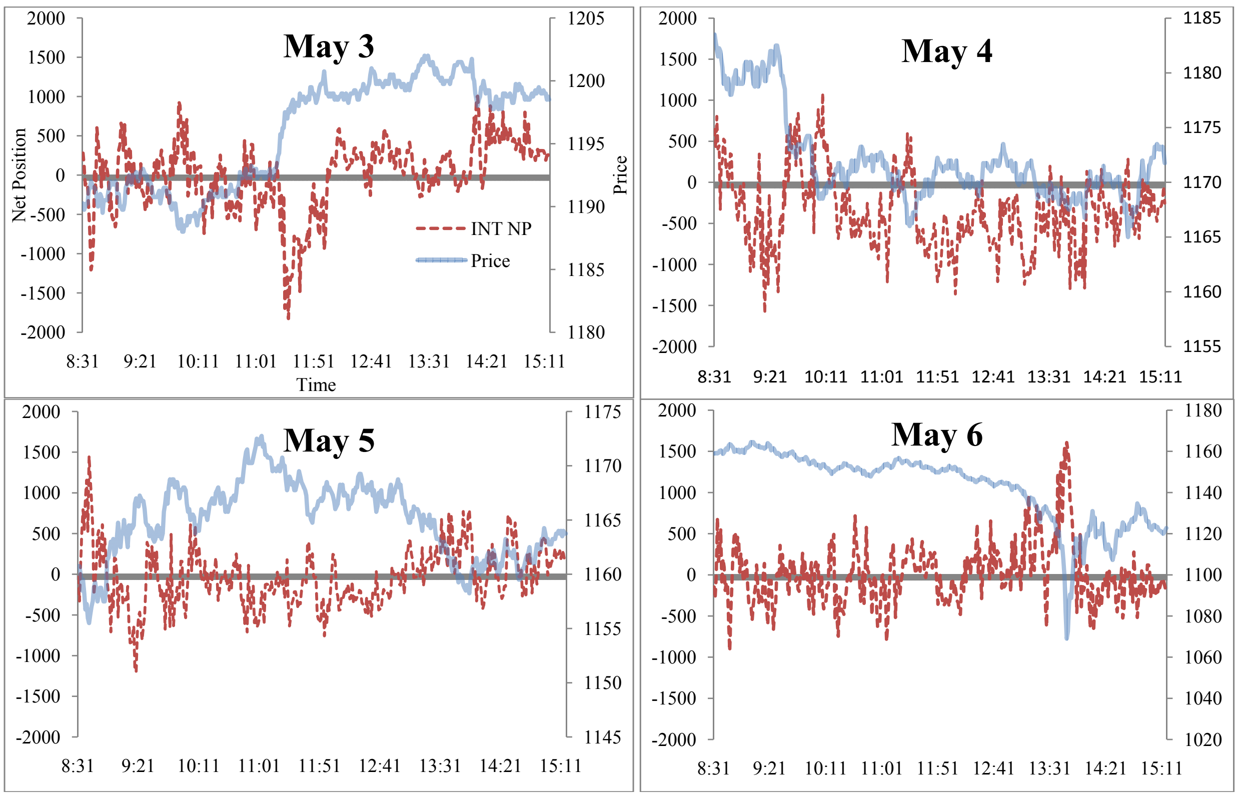
This figure presents trader categories superimposed (as shaded areas) over all individual trading accounts ranked by their trading volume and net position scaled by market trading volume. The figures reflect trading activity in the June 2010 E-Mini S&P 500 futures contract for May 3-6, 2010.

Figure 4: Net Position of High Frequency Traders



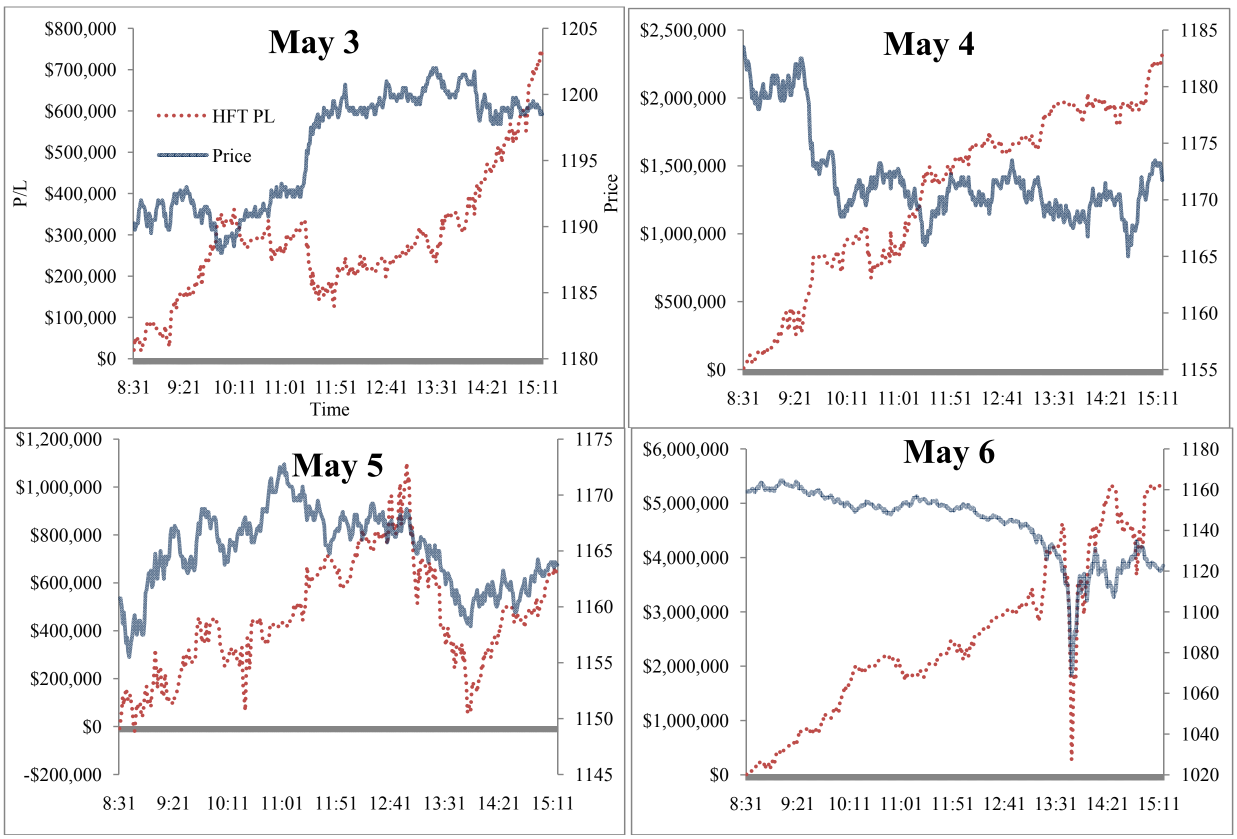
This figure presents the net position of High Frequency Traders (left vertical axis) and transaction prices (right vertical axis) in the June 2010 E-Mini S&P 500 futures contract over one minute intervals during May 3,4,5, and 6 between 8:30 to 15:15 CT. Net position is calculated as the difference between total open long and total open short positions of High Frequency Traders at the end of each minute. Transaction price is the last transaction price of each minute.

Figure 5: Net Position of Intermediaries



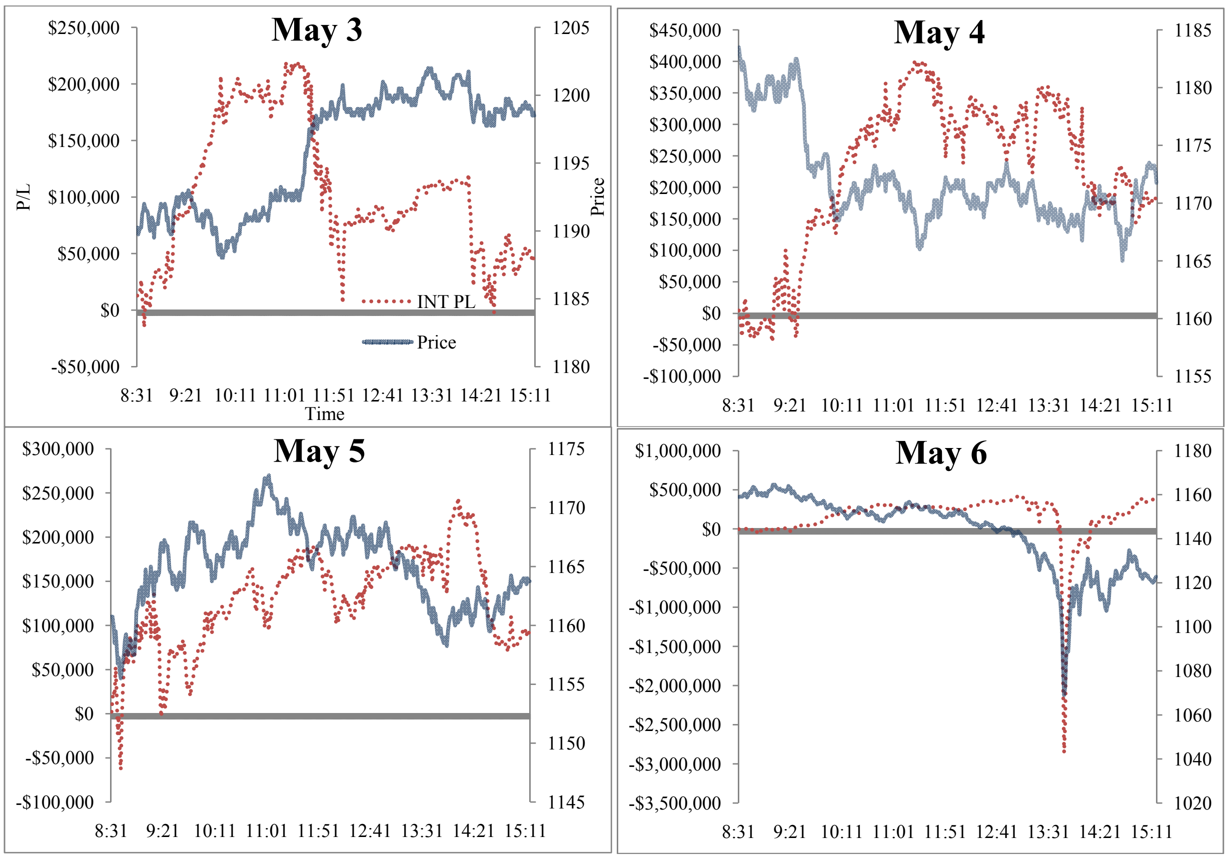
This figure presents the net position of Intermediaries (left vertical axis) and transaction prices (right vertical axis) in the June 2010 E-Mini S&P 500 futures contract over one minute intervals during May 3,4,5, and 6 between 8:30 to 15:15 CT. Net position is calculated as the difference between total open long and total open short positions of Intermediaries at the end of each minute. Transaction price is the last transaction price of each minute.

Figure 6: Profits and Losses of High Frequency Traders



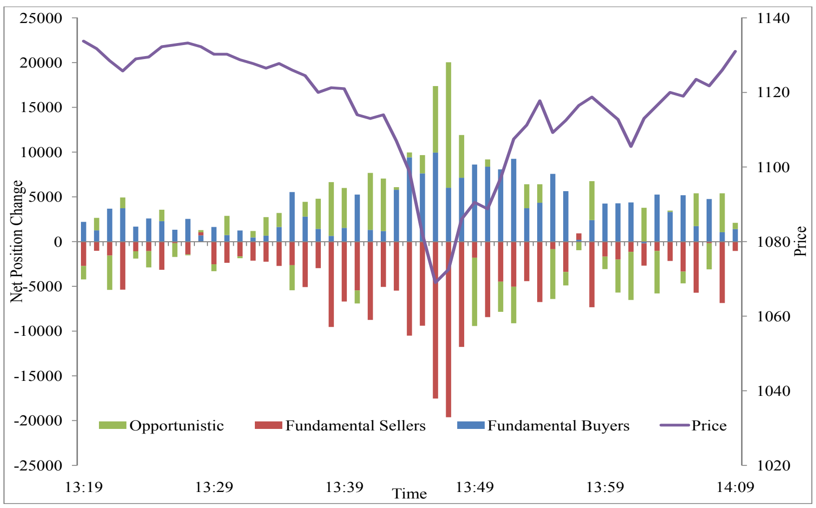
This figure presents the profits and losses of High Frequency Traders (left vertical axis)in the June 2010 E-Mini S&P 500 futures contract reported over one minute intervals during May 3,4,5, and 6 between 8:30 to 15:15 CT. Profits and losses are calculated by multiplying lagged net position by the change in price.

Figure 7: Profits and Losses of Intermediaries



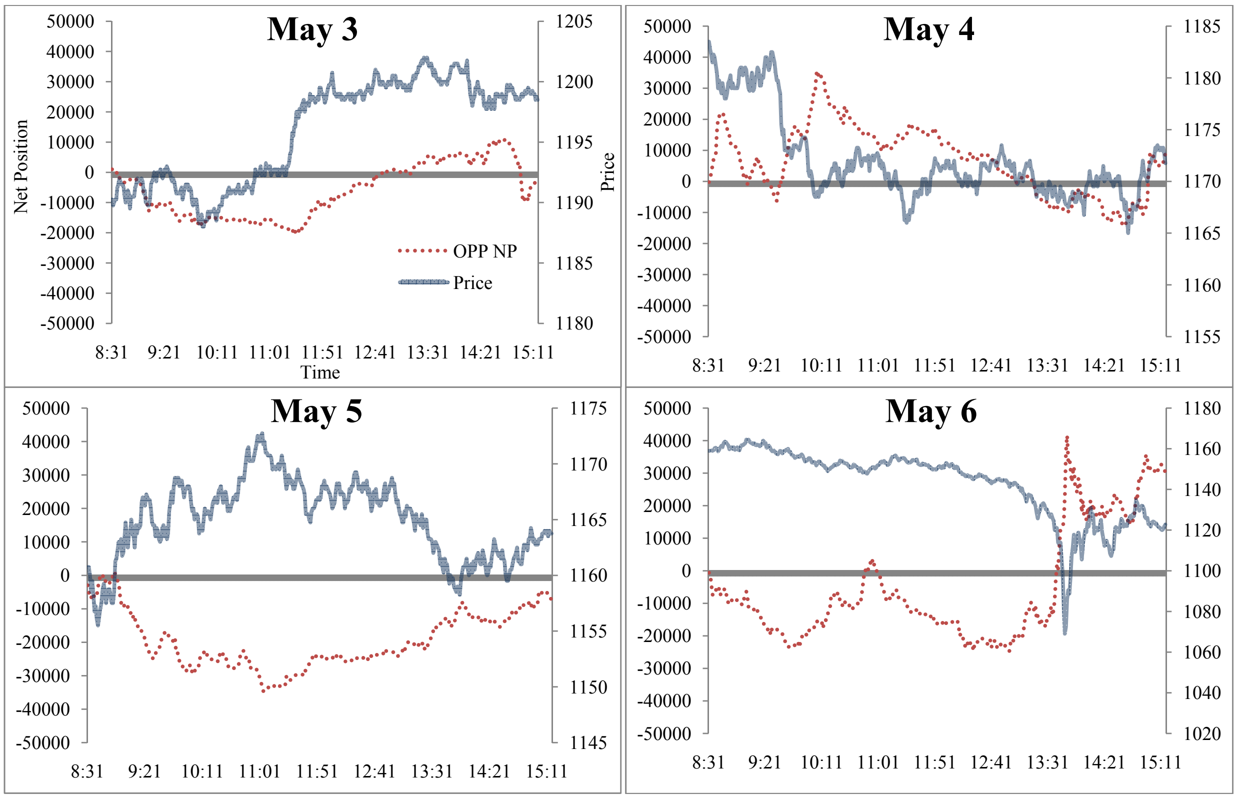
This figure presents the profits and losses of Intermediaries (left vertical axis)in the June 2010 E-Mini S&P 500 futures contract reported over one minute intervals during May 3,4,5, and 6 between 8:30 to 15:15 CT. Profits and losses are calculated by multiplying lagged net position by the change in price.

Figure 8: Change in Net Position of Fundamental and Opportunistic Traders



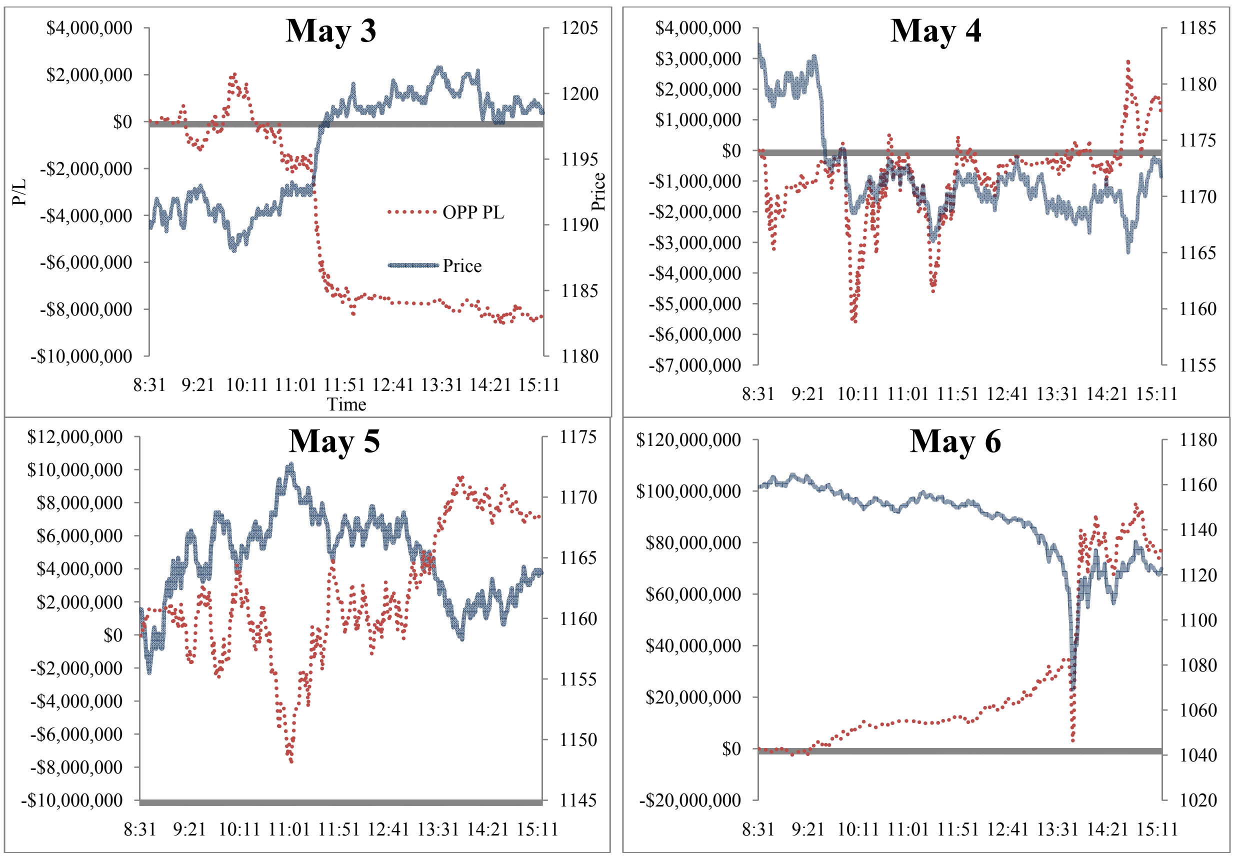
This figure presents the change in net position of Fundamental and Opportunistic Traders (left vertical axis) and transaction prices (right vertical axis) in the June 2010 E-Mini S&P 500 futures contract over one minute intervals on 6 between 13:19 to 14:09 CT. Net position is calculated as the difference between total open long and total open short positions of Opportunistic Traders at the end of each minute. Transaction price is the last transaction price of each minute.

Figure 9: Net Position of Opportunistic Traders



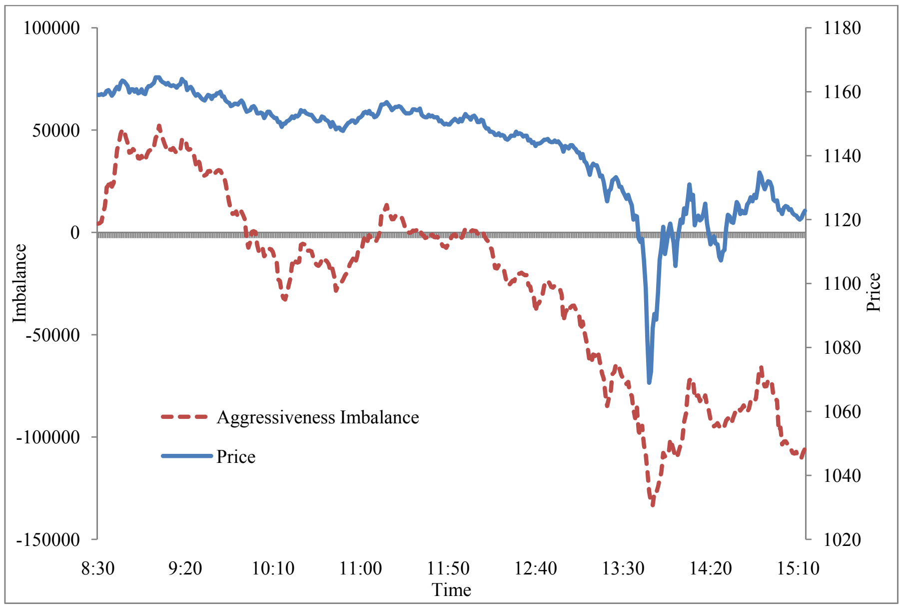
This figure presents the net position of Opportunistic Traders (left vertical axis) and transaction prices (right vertical axis) in the June 2010 E-Mini S&P 500 futures contract over one minute intervals during May 3,4,5, and 6 between 8:30 to 15:15 CT. Net position is calculated as the difference between total open long and total open short positions of Opportunistic Traders at the end of each minute. Transaction price is the last transaction price of each minute.

Figure 10: Profits and Losses of Opportunistic Traders



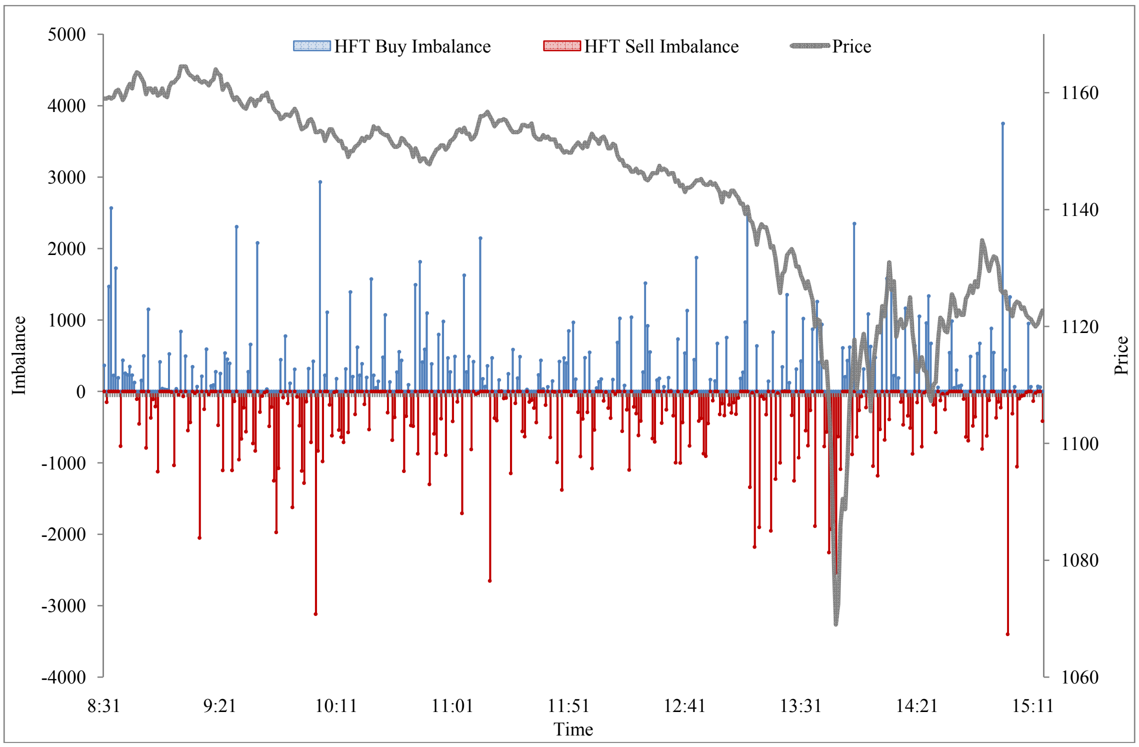
This figure presents the profits and losses of Opportunistic Traders (left vertical axis)in the June 2010 E-Mini S&P 500 futures contract reported over one minute intervals during May 3,4,5, and 6 between 8:30 to 15:15 CT. Profits and Losses are calculated by multiplying the lagged net position by the change in price.

Figure 11: Total Aggressiveness Imbalance



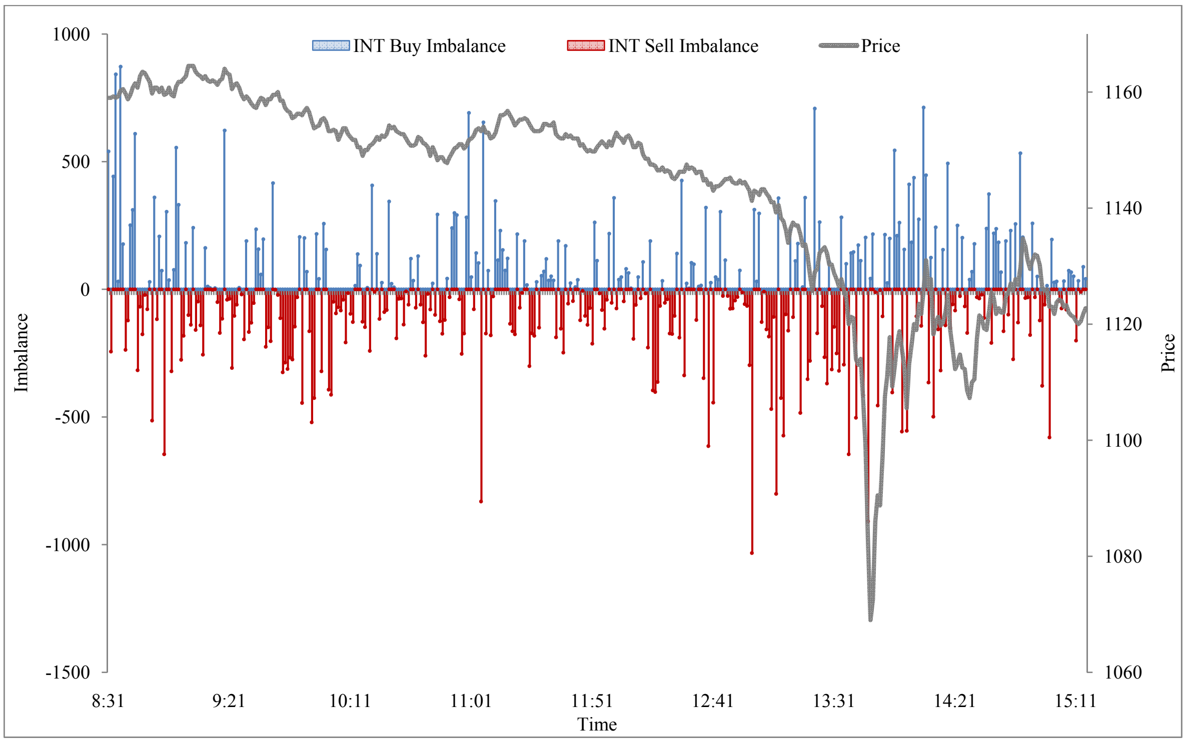
This figure presents the Total Aggressiveness Imbalance and prices in the June 2010 E-Mini S&P 500 futures contract over one minute intervals between 8:30 to 15:15 CT on May 6, 2010. Aggressiveness Imbalance is calculated as cumulative total aggressive Buy transactions minus cumulative total aggressive Sell transactions at the end of each minute. Price is the last transaction price for each minute.

Figure 12: Aggressiveness Imbalance of High Frequency Traders



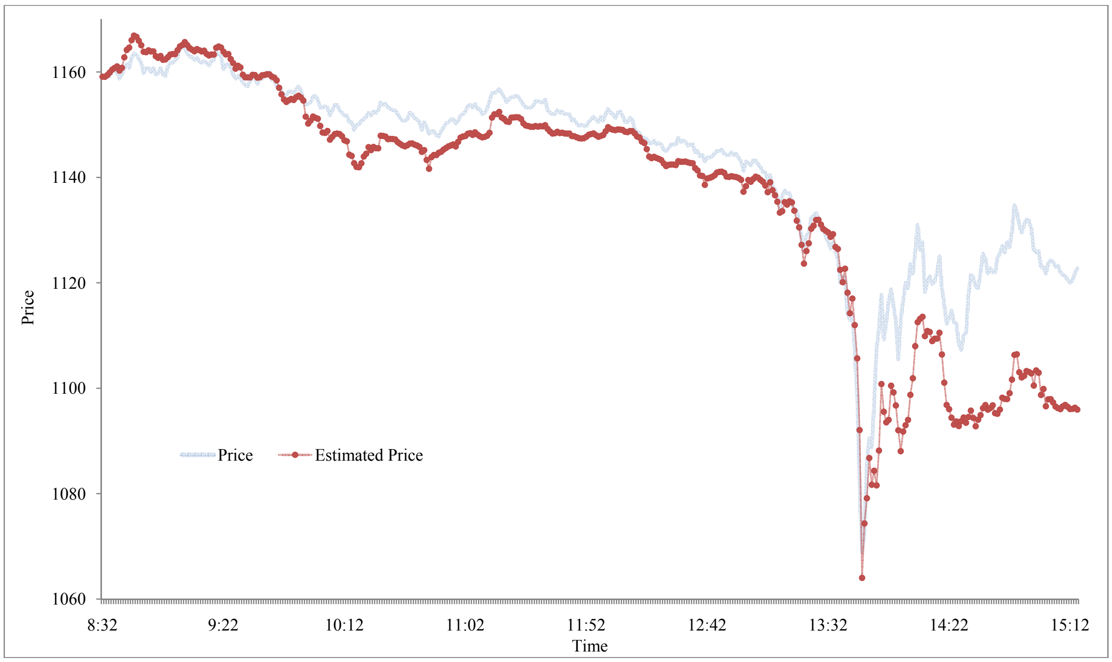
This figure presents the Aggressiveness Imbalance of High Frequency Traders (HFTs) and prices in the June 2010 E-Mini S&P 500 futures contract over one minute intervals between 8:30 to 15:15 CT on May 6, 2010. Aggressiveness Imbalance of HFTs is calculated as cumulative HFT aggressive Buy transactions minus cumulative HFT aggressive Sell transactions at the end of each minute. Price is the last transaction price for each minute.

Figure 13: Aggressiveness Imbalance of Intermediaries



This figure presents the Aggressiveness Imbalance of Intermediaries and prices in the June 2010 E-Mini S&P 500 futures contract over one minute intervals between 8:30 to 15:15 CT on May 6, 2010. Aggressiveness Imbalance of Intermediaries is calculated as cumulative aggressive Buy transactions of Intermediaries minus cumulative aggressive Sell transactions of Intermediaries at the end of each minute. Price is the last transaction price for each minute.

Figure 14: Fitted Price Based on Estimation of Market Impact



This figure presents actual and fitted prices in the June 2010 E-Mini S&P 500 futures contract over one minute intervals between 8:30 to 15:15 CT on May 6, 2010. The Solid line is the last actual transaction price for each minute. The Marked line is the fitted price calculated by applying estimated coefficients from market impact regressions (Equation (3)) using data for May 3-5, 2010 to realized Aggressive Imbalances of different trader categories on May 6, 2010.